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Scarcity and the Theory of Storage in Commodity Markets

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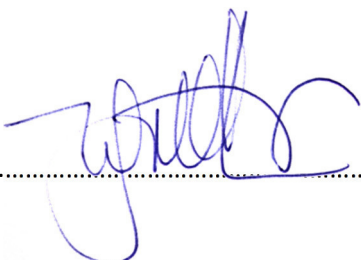
Submitted for the degree of

Doctor of Philosophy of the University of London

September, 2012

Declaration

I confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Signed, ....., William Owen Smith.

Abstract

For most of the 20th century commodity prices fell in real terms. Prices of metals, energy and food became so low that they were almost irrelevant to developed world consumers. Since 2003 prices have risen sharply, and have become so high they have been blamed for recessions, civil unrest and even revolutions.

Although increased speculation in commodity markets has probably played a role, the fundamental factors of supply and demand continue to form the most important determinant of commodity prices. Price rises have been caused by 'scarcity' caused by rapid demand growth from newly affluent consumers in the developing world, meeting a supply that has struggled to respond. Understanding current and future scarcity in commodities therefore helps us predict and warn of further price spikes. This thesis studies all three major commodity groups, examining existing ways to measure scarcity and proposing new ones.

Firstly we study the base (industrial) metals. We examine the 'theory of storage', which explains price and price volatility in terms of the quantity stored in inventory, a key measure of scarcity.

Secondly we study energy markets. Electricity cannot be stored, so the 'theory of storage' cannot be applied. We note an alternative measure of scarcity which allows us to apply a modified theory of storage to electricity. We also examine its applicability to another key energy commodity, crude oil.

Finally we examine scarcity in the agricultural products. Here we have inventory data, providing short-term scarcity information, but unlike for energy and metals, we have no concept of reserves, being that resource known but remaining in the ground, which provides longer-term scarcity information. Instead, we propose and examine several other ways to measure scarcity.

Acknowledgements

This thesis is the result of my work as a PhD student under the supervision of Prof. Hélyette Geman at Birkbeck, University of London.

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Additional thanks go to the various other Birkbeck research students who have stimulated my ideas, as well as the administrative staff who work diligently behind the scenes, to the extent that my entire PhD time has been free to spend on research.

I thank Prof. Chris Gilbert for assistance with obtaining historical data for metals, and the participants of the London Graduate School in Mathematical Finance Symposium 2011 and 2012 for their comments.

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Thanks also to journal editors and anonymous reviewers for their thankless tasks, and to all those who have taught me mathematics. I gratefully acknowledge a College Research Studentship from Birkbeck College.

Finally, thanks to all those (including myself) who produce open source software and open content, such as the indispensable Wikipedia.

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Chapter 1

Introduction

The Fall and Rise of Commodity Prices

The 20th Century – The Fall

During most of the 20th century, prices of most commodities fell in real terms. Increasingly affluent consumers in the developed world enjoyed a time of plenty, as technological innovations and economies of scale made energy production, metals production and farming into huge and efficient industrial processes.

For a first example, we consider the most heavily traded and studied commodity, crude oil. In the 19th century, crude oil was little more than a novelty, produced and consumed in tiny quantities, mainly to make kerosene for use in lamps. The oil age truly began in 1901, on the supply side with the discovery of the famous ‘Spindletop’ oil well in Texas, which initially produced as much oil as all prior wells worldwide combined (Roberts 2005). On the demand side, the era of mass-produced automobiles began in 1903 when Henry Ford introduced his Model A.

Apart from a brief rise during and after World War I, real oil prices fell throughout most of the 20th century as more efficient production techniques and gigantic new discoveries, mainly in the middle-east, came online. By 1965, oil provided mankind with more energy than any other fuel (BP 2012). The 1973 oil crisis, caused by events in the Middle East, marked the only major deviation from the downward trend in prices, with elevated prices continuing until around 1986. From then until 2003, oil prices remained at \$40 or below in 2011 US\$. Cheap oil had returned, and having already adapted their houses and cars to use much less energy in the 1970’s, consumers once again barely cared about the cost of energy. Only since 2003 has the price of oil and energy again made the headlines and become once more a concern for the ordinary citizen.

A similar story holds true for the other two branches of commodities, agriculture and metals. They too saw a decrease in real prices during the 20th century, although the extent of this decrease depends on the choice of deflator (Svedberg and Tilton 2006). Both agricultural commodities and metals have seen a spike upwards beginning in 2004 (metals) and 2007 (food).

The low commodity prices that persisted during the late 20th century were good news for consumers, and good news for economies that thrived on cheap energy. Only commodity producers and investors in their companies fared badly. Commodities were unfashionable, not particularly profitable, and investment in extraction and production fell. The average price

for crude oil in 1998 fell to an extremely low (nominal) price of \$12.72, a figure unseen since the early 1970's.

The Post 2003 Period – The Rise

Much has been written about the rise in commodity prices since 2003, and many explanations put forward, most with some credence. We summarize the main reasons below:

- Probably the major cause was the rise in demand for all commodities caused by the rapid growth in middle-class consumers in the developing world, particularly but not exclusively in the 'BRIC' countries, identified in 2001 as the engine of world economic growth for the decade that was to follow (O'Neill 2001). These new consumers purchased their first automobiles and filled their newly built urban houses with new 'white goods', using vastly more energy and metals than had been used by previous generations. Richer people tend to eat more meat, which in turn requires much more land and crops to grow than the mainly vegetarian diet of their parents; this trend was particularly marked in East and South-East Asia, where the per-capita consumption of meat rose more than 400% between 1975 and 2005 (FAO 2009, p.22). Analysing prices over more than one century, it is possible to identify the recent price rises as the beginning of a 'super cycle', with an expansionary phase lasting 10 years or more (Cuddington and Jerrett 2008).
- The low commodity prices seen in the decades up to 2003 had created a situation of underinvestment in new production; hence the supply side was 'taken by surprise' and unable to grow fast enough.
- Not only was production struggling to match demand, but elsewhere in the supply chain constraints were emerging, for example the lack of sufficient bulk-carrying ships to transport coal, metal ores and agricultural products, compounded by insufficient port capacity, which led to port congestion, exacerbating the lack of ships as they sat at anchor, queuing to load or unload rather than immediately travelling from source to destination. We examine commodity supply chains and their potential constraints below.
- Certainly in the case of energy, and possibly for metals and agriculture, the "low hanging fruit" had been plucked – the easy-to-find oil and minerals had already been found and much of it extracted, so production costs were beginning to rise. In the case of agriculture, the most productive agricultural land was already in use, and acreage growth was slowing (FAO 2011, p. 244).

- The high price of oil, rising from an average of \$25 (2002) to \$38 (2004) and then \$54 (2005) fed through into other energy products due to substitution; this price rise in all energy products then fed through into non-energy commodities due to many linkages. Such linkages include fuel for the transportation of commodities, electricity for the smelting of aluminium and other metals, and the use of natural gas to produce artificial nitrogen-based plant fertilizer. The rise in the politically sensitive price of automotive fuel in turn created the biofuel industry, which hoped to create a second source of energy supply from agricultural products. This in turn led to a sharp rise in agricultural prices from 2007 onwards.
- The entry of new market participants into financial commodity markets, such as hedge funds, and the increasing financialization of commodity products, with 'ETFs' and later 'ETNs' allowed private investors for the first time to buy commodities with the simplicity of equities. In some cases, in particular gold, the new non-commercial players had a 'buy-and-hold' strategy, accruing physical commodities; this became without doubt a source of additional demand. In other cases (notably crude oil), the new players bought financial futures and sold them prior to expiry since they did not wish to take physical delivery. Whether this contributed to price rises has been hotly debated, since net demand did not rise, almost certainly it did cause an increase in price volatility.

In summary, most of the post-2003 rise in commodity prices can, we believe, be attributed to fundamentals of demand exceeding supply, i.e. due to scarcity. Let us examine what we mean by this.

Scarcity

The word scarcity, used in our title, is used in general terms to describe something that is not as plentiful as we would like. The price of a commodity is inherently a function of supply and demand. If supply is constrained for any reason, scarcity of the commodity will result and prices will rise. The post-2003 commodity price rise, with the peak in mid-2008, is at least partly to blame for the resulting global recession which began in late 2008, with its after-effects still felt to this day. More recently, high food prices have been partly blamed for the civil unrest that occurred in many countries in 2011, culminating in the "Arab Spring" and the overthrow of many governments.

Studying how scarcity arises, and how commodity prices respond, is clearly not simply of academic or financial interest, but of crucial importance for a peaceful and stable world. In this light, it is unsurprising that the European Commission, the decision-making body of the European Union, should require a Scientific Advisor on Agricultural Commodities, indeed this role is performed by my esteemed PhD supervisor, who has been studying scarcity in commodity markets for many years.

Commodity Supply Chains

To understand commodity prices and how scarcity can emerge causing prices to rise, it is useful to review the commodity supply chain.

A Generic Supply Chain

Figure 1 below shows the supply chain of a generic commodity. We will examine this first and then examine how various real world commodities conform or deviate from this pattern. We discuss in each case the result of constraint or scarcity.

Note three different types of stage – transportation stages, processing stages and storage stages.

Moving across the diagram left to right:

Resources represent a non-renewable commodity in its raw form. Typically such resources are underground. The quality and quantity of the resources are not yet fully known (represented in Figure 1 by a blurred outline to this stage). For some commodities such as coal, resources are widespread and thought to exist in huge quantities. If resources are scarce then the next stage, discovery, becomes more difficult and expensive and ultimately we must consider the commodity to be ‘depleted’ and examine how this can be mitigated.

Discovery is the process by which resources are converted into known reserves, by detailed mapping and measuring of their extent and quality. No physical movement of the commodity takes place at this stage, it still remains underground. If discovery happens slower than current consumption (the so-called replacement rate) then the quantity of reserves will fall over time, raising concern about long-term scarcity.

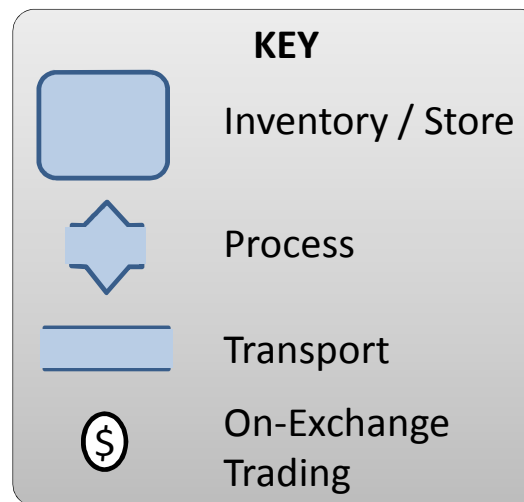
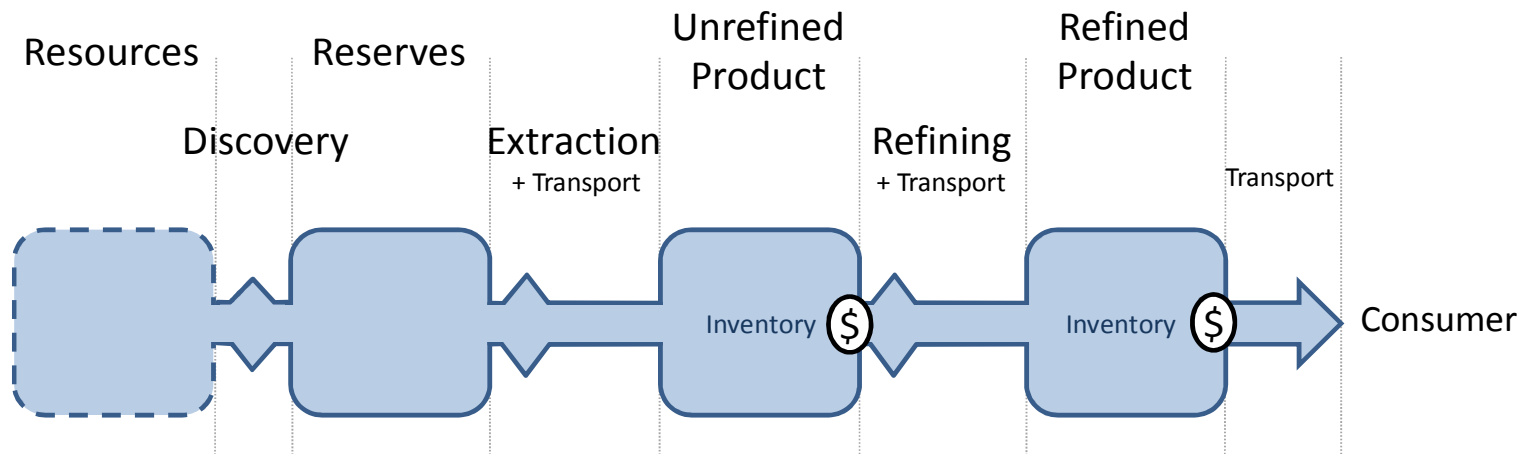


Figure 1 – A Generic Commodity Supply Chain

Reserves are raw commodities still underground but with a quality and quantity well known. The exact dividing line between resources and reserves is usually a legal distinction. Typically ‘proven’ reserves must be *economically* extractable at current prices. If reserves (typically measured in decades) begin to fall then this may affect prices, but typically futures markets only trade a few years out and are relatively unaffected by revisions to reserves values, provided that reserves are a considerable multiple of annual consumption.

Extraction is the process of bringing the raw commodity to the surface. Over the last 50 years this has become much more difficult for many commodities, because the reserves are in technically more inaccessible locations, or because the reserves are of lower quality (e.g. lower grades of ore in mines). Extraction is the first stage where constraints can have an immediate and large effect on price, for example a miner’s strike at a major mine. In some cases *spare capacity* exists in extraction, where the extraction rate is deliberately kept below its maximum possible rate (for example by mothballing mines), typically to support prices.

Transport takes the raw commodity from the point of extraction to an inventory store. Usually we take this for granted, but it can become a constraint if insufficient ships are available, if pipelines are overloaded or even break, etc. If this occurs it may affect the prices ‘downstream’, especially if inventory is low (see next item).

Unrefined Product is often stored in inventory after extraction. Sometimes the commodity is traded in its raw form (for example, crude oil). If this occurs, then the quantity held in inventory has a strong influence on price, and its value is closely followed by market participants. The relationship between inventory and price (as well as price volatility) is described in the *theory of storage*. Summarizing this, if inventory levels fall to unusually low values, prices will rise as will price volatility. If there are further traded products downstream, these may also rise in price, especially if their inventory is also low.

Refining converts the raw commodity into a refined form. For example, crude oil is refined into various oil products (gasoline, diesel, heating oil etc) and raw metal ores are refined into pure metal rods. In some cases (especially aluminium) refining takes lots of energy, this may too be constrained. To account for seasonal variations in demand, it may be necessary to have spare refining capacity. If refining capacity becomes constrained then prices of the refined product are likely to rise, while inventory of the unrefined product may build up.

Transport also often takes place after refining. Again, if transport becomes constrained then prices are likely to rise.

Refined Product is also stored in inventory. Typically refined products are again sold on-exchange. Again, the theory of storage predicts that if inventory is low, (refined product) prices and price volatility will rise. This will especially be the case if no spare capacity exists in refining or extraction, and if unrefined product inventories are also low.

Transport once again moves refined product onwards to consumers or to final assembly.

In summary there are three possible types of constraint that may cause scarcity of the commodity and raise prices.

1. A constraint in any one of the *processes* may restrict the transformation of the commodity as it moves through the supply chain. Ideally there will be some spare (idle) capacity available in each process to allow it to rapidly expand if required.
2. Transport constraints between each stage may restrict the flow.
3. Finally, each inventory/store stage should be adequately full to provide a buffer against supply and demand variations.

Typically constraints towards the early part of the supply chain will not affect prices as much as constraints towards the later parts of the chain.

We should also remember that the supply chain is not, in reality, a single path. Resource and reserves are found in many places, there are multiple refineries, multiple locations storing inventory, multiple consumers etc. Clearly the more choices for a given stage in the supply chain, the more tolerant the supply chain becomes to disruption.

The Metal Supply Chain

Firstly we review the metal supply chain (Figure 2) since it is closest to the generic supply chain discussed above.

We consider the case of aluminium, most other metals are similar.

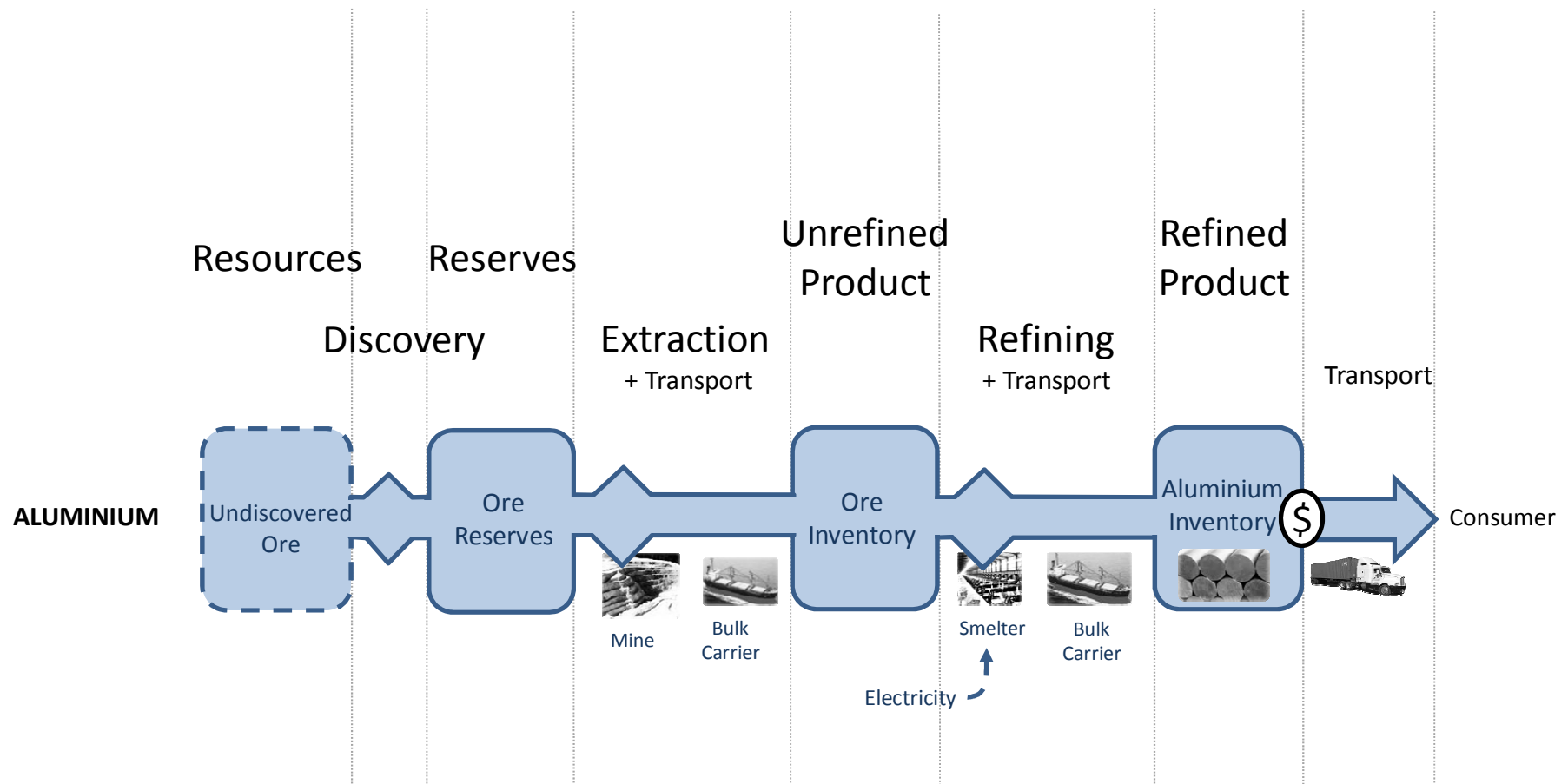


Figure 2 – The Commodity Supply Chain for Metals – the Case of Aluminium

Unrefined metals are called ‘ore’. The relationship between resource and reserves is perhaps more complex for metals than for say crude oil. Many metals are found in low concentrations throughout large areas, with a certain concentration required for economic extraction which depends on market price and extraction costs. Ever-improving mining technology makes extraction cheaper; there is a constant battle between this effect and the extra cost imposed by declining ore grades as the best deposits are exploited (Tilton 2002). Since it takes some years to open a new mine, there can be long lags between rises in metal demand and corresponding supply increases, causing multi-year periods of scarcity and high prices. Conversely, in times of over-supply, mines are often mothballed if market prices drop below their cost of production; this is currently happening in South Africa (platinum) and Indonesia (tin). This creates spare production capacity. Unfortunately exact production capacities and the presence of any spare capacity are usually commercial secrets, frustrating the analysis of spare capacity in metals.

In the case of most metals, the unrefined product is not traded on-exchange. Raw ore inventories exist in the supply chain but the quantities held in such inventories are typically not published.

Aluminium is interesting because of the vast amount of electricity required during the refining (‘smelting’) process. Because of this, ore may even be transported to locations with cheap electricity (often hydro-power), smelted (refined), and the refined aluminium transported onwards to market.

Seasonality complicates the supply chains of energy commodities (seasonality of demand) and agriculturals (seasonality of supply) and influences and complicates pricing. However, metals exhibit little or no seasonality. For this reason we begin our study with the industrial metals in Chapter 2, allowing us to construct a framework upon which we can build, before we study the cases of energy and agricultural products.

The Energy Supply Chains

Energy commodities exhibit more complex and diverse supply chains. We cover three representative examples in Figure 3. Firstly, we examine the case of crude oil and its refined products (we use the example of gasoline). Secondly we cover natural gas, and finally electricity.

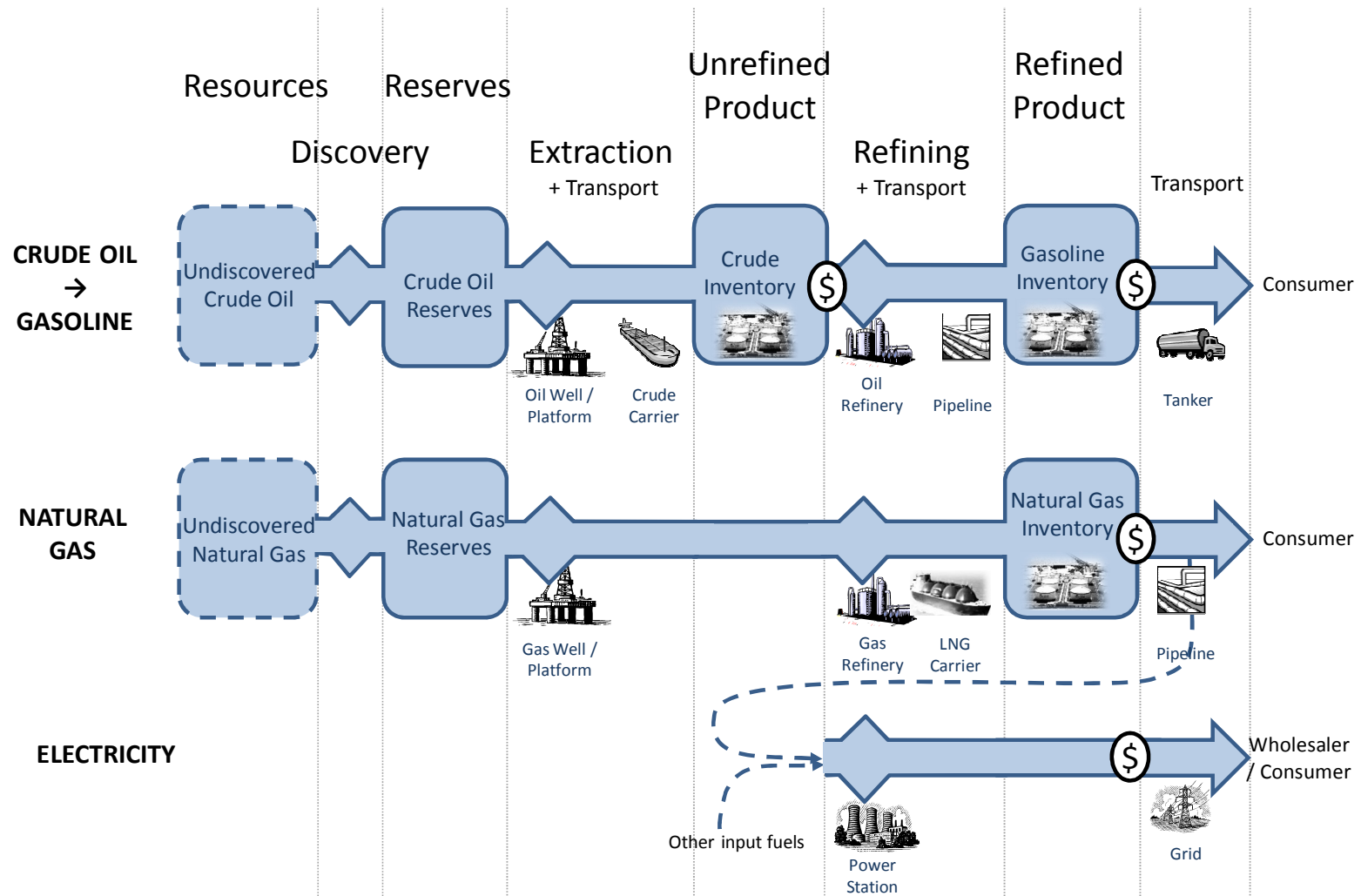


Figure 3 – The Commodity Supply Chain for Energy – the cases of crude oil and its refined product gasoline, natural gas, and electricity.

Crude oil confirms relatively well to the generic supply chain. *Resources* and *reserves* are widely distributed, although around 75% of proven reserves are in OPEC countries, pointing to the continued importance of OPEC in world oil production. The quantity of oil reserves remaining, and the likely rate of future discovery and drawdown of reserves provokes vigorous, even passionate debate. On the one hand many (Campbell and Laherrère 1998; Bentley 2002; Deffeyes 2006; Aleklett et al. 2010) argue that reserves are becoming scarce and oil production must soon decline based on the growth-and-decline curve first proposed by Hubbert (1956). Others (Watkins 2006; CERA 2006; OPEC 2011) paint a more rosy picture with oil production able to rise for some decades, before eventually plateauing. Reserves data, and particular reserves revisions, are hard to incorporate into models since the details are often national secrets; in particular the near-simultaneous doubling of stated reserves in many OPEC countries in the mid-1980's, with barely any variation since then, despite huge consumption, casts doubt on OPEC's data. It appears to us that claimed reserves values, at least in the case of OPEC, are influenced more by geopolitics than by accurate fundamentals. For that reason we excluded reserves from our analysis after lengthy consideration.

Extraction of oil is increasingly technically difficult; with most on-shore wells now depleted, attention has turned offshore; the blowout of BP's "Deepwater Horizon" in 2010 provided a reminder of the risks involved. There usually exists some spare capacity in the extraction process. This is important since crude oil extraction is a capital intensive industry with long lead-times; it takes some years after discovering an oil field before it can be brought online. This is especially true for the most recently discovered oil fields, such as those off Brazil underneath both very deep water and several miles of salt; full oilfield development there is expected to take over 10 years from their initial discovery, due to the extreme technical difficulty of extraction oil at such depths.

The *transport* of crude oil after extraction is another potential source of constraint, leading to downstream scarcity. Typically there are plenty of crude oil tankers available, although there may be localized issues (for example, the recent EU restrictions on insuring oil tankers carrying Iranian oil has made it more difficult for Iran to export oil).

Crude oil is widely held in *inventory* (i.e. in its unrefined state), as well as traded. The inventory data are very closely followed by market participants. In the US, the weekly US inventory data release at 1030am EST each Wednesday is so closely followed that oil prices often fall or rise sharply in the seconds and minutes afterwards. This inventory value is used as a key bellwether of US crude oil demand and more generally the state of the economy. Many

papers and effort have been devoted to studying the relationship between crude oil inventory and prices. This motivated our interest in using *other* measures of scarcity in a model for crude oil prices.

Crude oil is *refined* into a number of oil refined products in oil refineries; one of the most important is gasoline. Sufficient refining capacity is another potential constraint that could lead to downstream scarcity. The utilization rates of US oil refineries has at times risen over 90% in recent years, and been partly blamed for high gasoline prices.

After refining, crude oil products may again be *transported* through pipelines or by road, either on the way to storage or to the final consumer. There are rarely constraints in this stage.

Gasoline *inventories* data are again widely followed, and their influence on prices widely studied. Gasoline, like crude oil is widely traded on-exchange.

Natural gas supply chains differ from those of crude oil in two major ways. Firstly, natural gas has no ‘unrefined inventory’ stage and is not traded in unrefined form. It is typically transported immediately from the extraction stage to a nearby processing stage where impurities are removed.

The second difference is its method of *transport*. Although we display in Figure 3 an LNG carrier (ships which carry natural gas which has been compressed and cooled to around -160 °C, and is therefore in liquid form), the majority of natural gas at the present time is transported in pipelines in its gaseous state. This seemingly small difference in transportation when compared to crude oil produces great differences in the industry. Pipelines are expensive to construct and ‘fixed’, so long-term supply contracts between buyer and seller are normally agreed to allow the investment costs to be recovered. Natural gas therefore tends to form regional markets related to pipeline networks. Consumers of natural gas supplied by pipeline face some risk of disruption (sometimes considerable risk) and hence scarcity. For example, many Western European countries receive most of their natural gas supply by pipeline from Russia, and have seen gas deliveries suddenly reduced several times in recent years due to disputes over pipelines revenues. One solution is to build additional pipelines from different source countries travelling on different routes. Greater diversification can be obtained by building liquefied natural gas (LNG) regasification plants, which allows gas to be

purchased at short notice from a number of alternative countries and transported by sea (Lefèvre 2010).

Natural gas *inventories* are again closely followed by market participants. Because natural gas consumption is strongly seasonal (used mainly for winter heating but also for electricity generation for summer cooling), inventories vary greatly through the year; studying inventory for signs of scarcity naturally requires some kind of data deseasonalization. The relatively high cost of gas storage also causes seasonal cycles in natural gas prices; these are not observed in crude oil.

Finally natural gas is once again *transported* to end-users by pipeline. The inventory and final pipelines are typically located in the country of consumption, so there is less risk of disruption.

Electricity is a unique and fascinating energy, again covered in Figure 3.

Firstly, electricity is *generated* in power stations using a choice of input fuels. We include this as a ‘refining’ stage since electricity is generated from input fuels in its fully-refined state, ready for consumption. Scarcity or constraints of input fuels therefore constitute the first risk that can cause electricity scarcity. For example, electricity in India is constrained by its lack of domestic crude oil and natural gas. While it has plenty of domestic coal, it is unable to extract it fast enough to meet the demand of the electricity industry.

The possibility of insufficient electricity generation capacity is another potential source of electricity scarcity. Indeed, it is important to maintain some spare generating capacity (this is known as reserve margin in electricity jargon). The chronic *under*-capacity in the Indian electricity industry, mentioned above, is a contributory factor to the huge recent power cut which affected 600 million people, surely the biggest power cut in history.

There is no *inventory* stage in electricity, due to its non-storable nature. We study this in Chapter 4.

Indeed, electricity is *transported* directly from the generation stage to consumers over a grid. This grid is also a source of constraint and may result in localized bottlenecks or even catastrophic grid failure if not properly planned and maintained, as was the case in the famous August 2003 power cut which affected both the USA and Canada. In particular, the introduction of larger amounts of intermittent renewable energy from sources such as wind and solar power is necessitating major upgrades to electricity grids.

The Agricultural Supply Chain

Finally we turn to the third and last major branch of commodities, the agricultural products. These all exhibit a similar supply chain, see Figure 4. The figure covers two different agricultural commodities, corn and the soybean complex. The only difference is that soybeans, as in our generic commodity supply chain of Figure 1, is traded in both unrefined form (soybeans) and refined form (soybean oil and soybean meal). In contrast, corn is traded only in its unrefined form, which is then sold directly to consumers. We describe therefore in more detail the more complex chain, that of soybeans.

Notable at the start of the supply chain is the lack of *resources*, and we have put a dotted line around the ‘*reserves*’ box to distinguish the agricultural case from our prior examples. Being essentially a renewable resource, there are no subterranean reserves of agricultural products for us to discover and convert into reserves. The closest we can get to the concept of reserves is to study in detail the various requirements of crops (soil, water, sunlight, nutrients, temperature) and to examine where on earth such requirements may be met, both now and in the future, and bodies such as the UN Food and Agriculture Organisation do exactly that (FAO/IIASA 2010).

We can perhaps then class farming as ‘*extraction*’; we use the agronomic resources available to grow crops then ‘extract’ them from the soil at harvest time. Agricultural productivity has increased over the years; yields (the quantity of crop produced per harvested area per year) have increased due to improved crop varieties with greater weed resistance, greater use of pesticides, fungicides and artificial fertilizers, more irrigation and many other technologies. However, yields are variable, mainly due to weather, and the progress of each crop from planting onwards is closely followed by financial markets. There is great debate concerning the quantity of unused land remaining for agriculture (i.e. spare production capacity), but the most informed estimates seem to say ‘not much’, with arable acreage projected to grow only 0.1% p.a. between 2005 and 2050 (FAO 2011, p. 244). We examine spare capacity from another angle in Chapter 4, proposing a way of estimating it based on *historical* acreage.

Like other commodities, agricultural products are *transported* from the farm. For overseas travel, bulk carriers are used. At times of high demand this can be a source of constraint and downstream scarcity, particularly if ports are also congested.

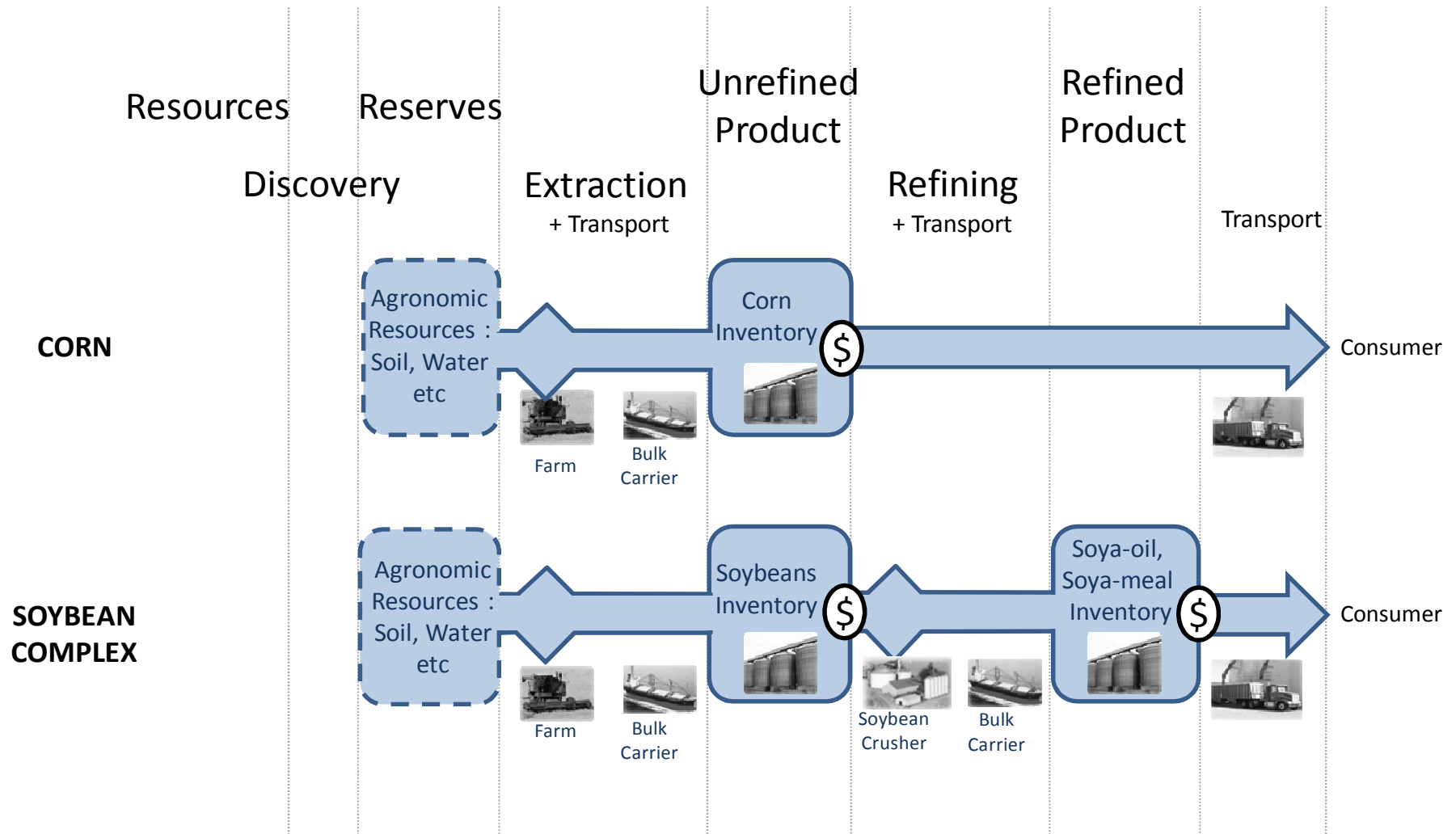


Figure 4 - - The Commodity Supply Chain for Agricultural Products

Agricultural *inventories* are again closely followed. Since supply is seasonal, inventories rise suddenly during the harvest then fall through the rest of the year (some harvests occur in both north and southern hemispheres roughly 6 months apart, reducing this effect). The most closely followed inventory figure is the lowest value for the crop year, shortly before the new harvest, this is called the ‘year-end carryover’. The FAO defines a year-end carryover of 17-18% of annual global consumption as the minimum “to safeguard world food security” (FAO 1996). It was this year-end carryover inventory figure that Working first studied, in the case of wheat, when he formulated the *theory of storage* (Working 1933).

In the case of some agricultural commodities such as soybeans, there is a separate processing stage to a refined product (‘crushing’ in the case of soybeans). Lack of crushing capacity could theoretically be a constraint, causing downstream scarcity. Refined product inventories are also monitored by market participants to warn of emerging scarcity.

Finally, agricultural products are *transported* to market, a final source of potential constraint and scarcity.

What We Study

Metals – Inventory

In Chapter 2 we study the classic theory of storage (Working 1933; Working 1949), looking at the relationship between refined-product inventory, price, and price volatility in the case of the six base (industrial) metals traded on the London Metal Exchange. Working showed that prices and volatility rise sharply when inventory falls to unusually low levels. Two previous influential papers examining the theory of storage and metals (Fama and French 1988; Ng and Pirrong 1994) were limited because actual inventory data were unavailable at that time. This data is now published, allowing us to fully examine both relationships proposed by the theory of storage (price vs. inventory, and volatility vs. inventory). We find that the theory of storage is strongly validated. Our results help us to define exactly which inventory data we should use. We also discover that a simple transformation of inventory data causes all six metals we study to behave quasi-identically. Recently, many metals warehouses worldwide have been purchased by several large financial institutions, and it is alleged that requests by other market participants to withdraw their metal from these warehouses are unfairly

delayed. Our results allow us to test whether markets display any distortion, which might validate these claims.

Energy – Inventory and Spare Production Capacity

Chapter 3 examines scarcity in the energy commodities. Having confirmed the value of inventory in our first chapter, we turn to another stage of the supply chain, looking at spare capacity. We examine the relationship between spare capacity and price, in the cases of both electricity and crude oil. For electricity we examine spare *generation* capacity, known as ‘reserve capacity’. For crude oil, we examine spare *production* capacity.

Why did we examine spare capacity? Firstly, observing the lack of inventory for electricity, we noted that the theory of storage cannot be applied. Models in any domain are to be preferred if they are unified and explain many situations. We thus set out to extend the theory of storage to include non-storable commodities such as electricity, and demonstrate how this can be done by using spare capacity in the place of inventory.

Secondly, we noted that oil markets and many oil models seem obsessed with using inventory as a sole indicator of scarcity. We noted the availability of data for spare crude oil production capacity, and that this spare capacity had fallen to very low levels during the price boom of 2004-2008. Spare capacity then rose sharply during the recession beginning in late 2008 as oil demand fell, coincident with the huge fall in oil prices at that time. We found that spare production capacity had been considered in early oil price models of the 1980s, but had fallen from favour since then. We therefore also tested in Chapter 3 whether spare capacity had explanatory power for crude oil prices, and found this to be the case.

Agriculture – Various Measures of Scarcity

We noted above that agricultural inventory values are already closely monitored by market participants, and studied by academics. Typically, year-end carryovers are only a small proportion of annual consumption, of the order of 10-30%. Thus inventory can only warn of scarcity in the 1-2 year timeframe, since a single terrible harvest could conceivably necessitate a drawdown of the entire worldwide inventory. We thus set out to examine other potential indicators of agricultural scarcity that may warn of scarcity in the medium term.

We examine in Chapter 4 the four main global agricultural products, corn, wheat, soybeans and rice. We propose a number of novel ways of measuring scarcity, seeking to compare scarcity between these four crops, and also to see how scarcity has evolved over time.

Firstly, we propose an econometric technique for estimating the level of spare production capacity for a given crop, i.e. how by much the planted acreage could conceivably expand in the next crop year, given sufficient price incentive. We show a strong relationship between price and this spare capacity, validating our methodology.

Secondly, we introduce the concept of ‘yield-at-risk’, analogous to ‘value-at-risk’ in financial risk modelling, and demonstrate how this puts inventory levels into better context.

We also note that diversity of supply eases risk to consumers. In order to quantify this, we examine an index of market concentration for each crop, for both production and exports.

Finally, we note that if spare land is available, even if marginal, crops will gradually expand to use it, especially at times of high prices. Conversely, if no additional land is available, the expansion of one crop will be at the expense of another, i.e. a situation of land scarcity and competition for it between different crops. We test for this using the four crops we study.

Summary

Our three investigative chapters cover all three major branches of commodities. We start in familiar territory, examining the theory of storage in the case of metals using inventory data. Moving to energy products, we use spare capacity, less studied than inventory, to detect scarcity and describe an extension to the theory of storage that allows electricity, a non-storable commodity, to be united with other commodities under a single theory. Finally, with agriculturals, we propose a novel way to estimate spare capacity, as well as proposing several other novel measures designed to detect agricultural scarcity in the medium term.

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Chapter 2

Theory of Storage, Inventory and Volatility in the LME Base Metals

Abstract

The theory of storage, as related to commodities, makes two predictions involving the quantity of the commodity held in inventory. When inventory is low (i.e. a situation of scarcity), spot prices will exceed futures prices, and spot price volatility will exceed futures price volatility. Conversely, during periods of no scarcity, both spot prices and spot price volatility will remain relatively subdued. We test these relationships for the six base metals traded on the London Metal Exchange (aluminium, copper, lead, nickel, tin and zinc), and find strong validation for the theory. Moreover, and in contrast to widespread claims that Chinese inventory data are opaque, we find that including Chinese inventories strengthens the relationship further. We also introduce the concepts of excess volatility, inventory-implied spot price and inventory-implied spot volatility and illustrate some applications.

This chapter is based on a paper I co-wrote with Prof. Geman, which was accepted by *Resources Policy* in June 2012, with publication date yet to be announced.

Introduction

The aim of this chapter is to examine the six base metals traded on the LME (aluminium, copper, lead, nickel, tin and zinc), and examine the relationship between price, volatility and the quantity held in inventory, for both the spot and futures markets. A relationship, believed to exist for many storable commodities, is predicted by the *Theory of Storage*. Firstly, we review briefly the base metals and futures trading. We then review the theory of storage and its literature across a number of commodities. We then review our data and develop a gauge for inventory which permits comparison between commodities and over long time periods. Next we examine the relationship between price and inventory, and the relationship between volatility and inventory. Finally we consider some applications.

Base Metals and Futures Trading

Firstly, we review the base metals, futures markets (particularly the London Metal Exchange) and the existing literature on the theory of storage.

The Base Metals

Unlike the precious metals such as gold and silver, which are often purchased for investment rather than commercial use, the base metals are all notable for their industrial uses, principally in automobiles (aluminium, nickel), packaging (aluminum, tin), building and infrastructure construction (aluminium, copper, nickel, zinc), electronic and electrical components (copper, lead, tin) and many other applications.

Prices of the base metals vary according to their rarity and extraction costs, ranging from around \$25,000 per tonne (nickel, tin), through \$10,000 per tonne (copper) down to around \$2,500 per tonne (aluminum, lead, zinc), observed in mid-2011. They are typically traded on the LME in the form of bars, rods or ingots, with the exact contract specifications being tailored to the typical requirements of industrial users, and at high purities in excess of 99.8%.

Unlike many commodities, the base metals show negligible seasonal variation in their supply and only minor seasonal variation in demand (related to slight variations in construction activity across the northern hemisphere year), simplifying their analysis. They are easily storable at relatively low cost (typically < 5% of their value p.a.), and unlike agricultural

commodities, suffer negligible degradation over time, again simplifying their analysis.

Futures Markets

Commodity markets typically have greatest liquidity in futures markets rather than spot markets, which allows participants to ‘lock in’ a price in advance, for example a farmer may wish to fix a price for his harvest long before harvest time, or a construction company may wish to fix the price of copper they will use some months hence. On any given trading date ‘ t ’, a number of futures contracts are traded, one for each maturity date T_1 to T_N . Typically maturities range from 1 month to several years into the future. The purchase of a futures contract obliges the owner to pay on the maturity date T_i , $i \in \{1, \dots, N\}$, the market price $F(t, T_i)$ to the seller, and in turn (s)he will receive one contract’s worth of commodities¹. Typically futures are traded on an exchange, and margin payments will be payable between the trade date t and the maturity date T_i to minimize the counterparty risk born by each side. In addition, for some commodities, spot markets exist with immediate delivery required. Where this is not the case, it is typical to consider the price of the futures contract which is soonest to expire (the so-called ‘front month’ contract) as a proxy for a spot price.

The London Metal Exchange

London has been the world hub of metal trading for centuries, in an area near to the former Royal Exchange. Ad-hoc metal trading was replaced with a formal exchange with the founding of the London Metal Exchange in 1877. The LME has remained the centre of world metal trading ever since. Despite competition from COMEX in the US, and the Shanghai Futures Exchange (SHFE) in China, it remains for now the most liquid venue for trading of base metals. In particular, we examine in this study its contracts for Aluminum, Copper, Lead, Nickel, Tin and Zinc.

¹ Typically there may be some small lag comprising several business days between maturity of the contract and the delivery date, but this is irrelevant in the present context.

The LME's trading structure is somewhat unique, resulting from its long history. Several times a day, so called 'ring' trading sessions occur, in an open-outcry format, with traders located physically in a seated circle or ring, with only a single metal traded per brief and intense 5 minute session. Electronic trading is also available during an extended business day, and telephone trading is available 24 hours per day, with all trades reported and settled through the LME (LME 2011).

Unlike most commodity exchanges where futures contracts are typically deliverable in fixed months, with only occasional 'expiry' of contracts, the LME trades constant maturity contracts. On each trading day, contracts for delivery in 2 days ('spot'), 3 months, 15 months and 27 months are traded. The 3-month contract is the most heavily traded, and was originally introduced because it took that long for tin from South-East Asia, or copper from Chile, to arrive by ship to London (Bloomberg 2011).

The LME maintains a worldwide network of over 600 warehouses. Although counterparties of a futures or spot trade are free to arrange bilaterally the delivery of metal from seller to buyer, they can also deliver to or take delivery from an LME warehouse. The warehouses are carefully chosen worldwide to be at sources of demand rather than supply, ensuring that the buyer has immediate access to the metal he has purchased (LME 2011b). However, to date, China does not allow warehouses in its territory to become LME-registered, and metal for Chinese delivery is typically shipped from Singapore or South Korea. Inventory figures across all warehouses are published daily.

Commodity Inventories and the Theory of Storage

Commodities can be categorized as storable or non-storable. Non-storable commodities include those where storage methods exist but are prohibitively expensive (in particular, the case of electricity) and where the commodity is the provision of a service (as in the shipping industry). The vast majority of commodities are storable. They are stored for several reasons:

- As a buffer against uneven or seasonal supply, as in the case of agricultural commodities, which have been stored in silos as early as 10,000 years ago
- As a buffer against uneven demand, as in the case of most energy commodities, which are typically used more in winter for heating, and midsummer for cooling

- As a buffer against any other supply or logistical disruption, which would otherwise necessitate the expensive pause of an industrial process
- In recent years, for investment purposes within physically-backed ETFs
- For arbitrage reasons, if any, as described later.

The theory of storage applies to any commodity that can be physically stored and makes two main predictions, both related to the quantity of the commodity held in inventory (also known as stocks, a term we avoid due to its confusion with equity markets).

Prediction 1, the Relationship between Spot and Futures Prices

When there is a situation of scarcity (low inventory), spot prices will rise as purchasers bid whatever is necessary to secure supply. The effect will be less pronounced in longer term futures, since market participants know that higher price will, in the long term, stimulate increased supply and allow for a rebuilding of inventory. The effect, with *spot price > futures price*, can be extreme, and is known as ‘backwardation’. An example of backwardation in the crude oil futures market is shown in Figure 1, taken from the time of high oil demand and rapid price rises in 2007. Oil contracts that mature (expire) in 40 or more months are priced around \$76, whereas those expiring within 1 month (so called ‘nearby’) futures are priced as high as \$89.

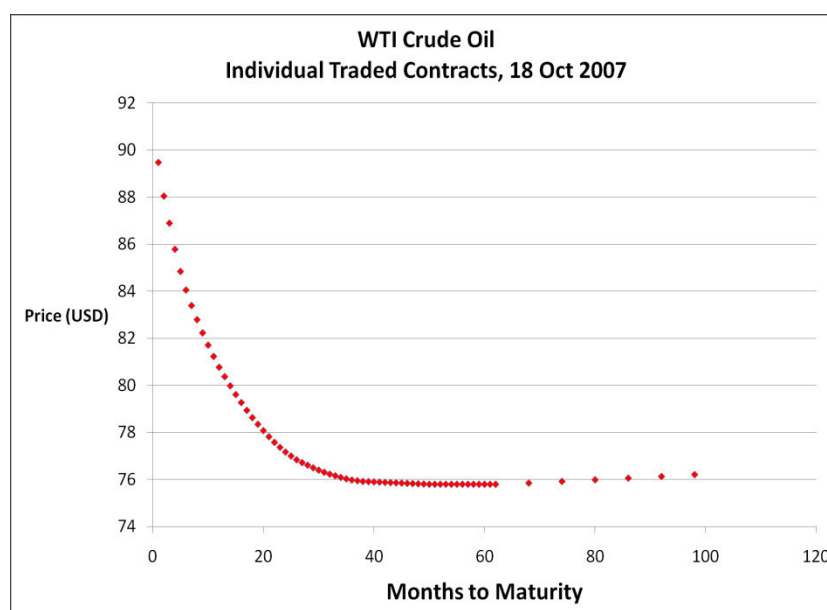


Figure 1 – Extreme Backwardation in the Crude Oil Market, 2007.

Conversely, when supplies are ample, spot prices can become depressed with respect to futures prices. However, this effect, with *spot price* < *futures price*, termed ‘contango’, is usually less pronounced. At a certain point, the possibility of so-called ‘cash and carry arbitrage’ emerges, whereby a risk-free profit can be obtained by buying the commodity in the spot market, simultaneously selling a futures contract at a higher price, and storing (‘carrying’) the commodity until the delivery date of the futures contract. This possibility limits the degree of contango for storable commodities. This effect is asymmetrical – we cannot move a quantity of commodity from the future to the present, therefore there is no economic limit on the strength of backwardation imposed by storage. However, given sufficiently high spot prices, some consumers will cancel or postpone their demand, or possibly substitute their demand to another commodity. This weaker economic argument provides some limit to the strength of backwardation.

Prediction 2, the Relationship between Spot and Futures Volatilities

In conditions of scarcity, not only will spot prices be elevated, but they will also experience elevated volatility. This is because in a tight market, any news about short term supply, demand or inventory will have a large impact on the spot market. However, there is little corresponding rise in the volatility of long term futures contracts, whose prices mainly respond to longer-term news.

In conditions of abundance, this effect will disappear, and there will be no pronounced difference between the volatility of spot and futures prices.

We note that in general, the so called ‘Samuelson effect’ (Samuelson 1965) states that commodity futures becomes more volatile as they approach maturity, although unlike the theory of storage, it does not mention that such conditions mainly apply during scarcity. We might expect that spot price volatility will almost always exceed futures price volatility, since long term prices mainly respond to long-term news, whereas short-term prices should respond to both short *and* long term news, as well as all kinds of “noise” induced by short term trading.

Development of the Theory of Storage –Inventory and Prices

We describe below the key architects of the theory of storage. In particular, early and instrumental work seems to be regularly overlooked in the literature.

Empirical observation of futures markets had long noted that near-month futures prices were often higher than long-term futures. Keynes (1930) first sought to explain the empirical data by noting that long term futures were usually sold by farmers wishing to fix a price for their harvest and therefore reduce their risk. The futures were bought by speculators, willing to take on the risk in order to realise a profit. Speculators would not enter the market, bearing risk, he argued, unless futures prices tended to rise as harvest approached, giving them a profit. Keynes' theory did not explain why the relationship he described seemed to vary from year to year, and in some years did not hold at all.

We attribute the initial development of the theory of storage to Holbrook Working. In 1927, he was a researcher at the recently established 'Food Research Institute' of Stanford University. The institute decided to focus on wheat because of its great importance as a world staple food (Johnston 1996). Little was formally known about the large fluctuations in the prices of wheat futures. Working theorized that the inventory levels of wheat, in particular the 'year-end carryover', being the inventory still existing at the end of one 'harvest year', just prior to the arrival of the new harvest, would be instrumental in understanding the behaviour of wheat prices. Since reliable wheat inventory data, or indeed inventory data of any commodity had not been collated and aggregated up to this date, Working and the Food Research Institute began to record new data and research previous years (Working 1927). By 1933, Working had sufficient inventory data, and in two profoundly important but rarely cited papers (Working 1933, Working 1934), he lays out in detail the concepts of the theory of storage, based on his empirical research on wheat. In the first paper, he describes in detail the futures markets in wheat and calculates price spreads between nearby and distant futures. The US wheat harvest occurs mainly from June to August, with the harvesting peaking in July. During the months of June and July, before the harvest had been transported to market, shortages of wheat sometimes developed. By September, the harvest was complete and for a time there was abundance. Working plotted the July-September spread (comparing pre- and post-harvest prices), as observed in June against the year-end inventory, see Figure 2 (reproduced using Working's original data), which we will henceforth term the "Working curve". A clear pattern emerged: in years of low inventory, the prices of July futures were much higher than September futures, resulting in a negative spread. In years with no

shortage, September futures were slightly more expensive, by an amount roughly equivalent to the additional cost of storing wheat for two months. This result, showing that short-term futures rise in time of scarcity, is Prediction 1. As well as this central result, Working also documented, we believe for the first time, some other features of futures markets:

- Information affecting next year's harvest (long term information) caused equal change in prices for July and September, resulting in no changes in spread. We would today term these as parallel shifts in the futures curve. Conversely, short-term information, about this year's harvest, affected short term prices (July) more than long term prices (September).
- The average weekly changes in price of July wheat (what we would now term volatility) varied more and more as harvest approached (the so-called Samuelson (1965) effect).
- In situations of scarcity, when July wheat rose in price over September, its volatility also rose greatly compared with situations of abundance (Prediction 2).

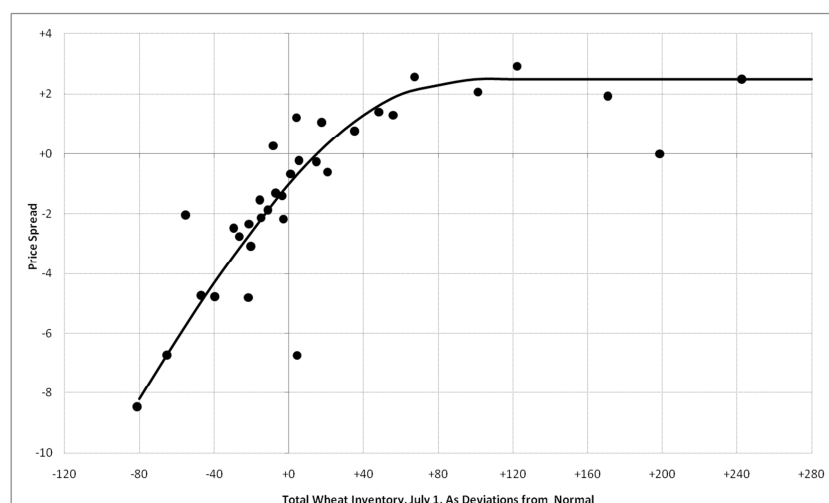


Figure 2 - Relationship in Wheat : Chicago July-September Spread in June, and Stocks on July 1, from Working(1933)

In the second paper, Working (1934) continued developing the theory of storage. He noted that representing the spread as a percentage rather than a dollar amount, in order to facilitate comparison across long time periods, did not diminish the relationship. He also noticed that the spread would build as harvest time approached, because a situation of impending scarcity or abundance only became clear towards the end of the crop year. Finally, he devoted attention to years that deviated from the usual trend, showing that 'corners' and 'squeezes' had occurred in those years, whereby inventory was bought and withheld from the market by a single participant with the aim of distorting the market for profit. Working

summarized his earlier work in two later papers (Working 1948; Working 1949), these sources are those normally cited.

Further intellectual development of the theory of storage was made by Kaldor (1939). Since Working's ground-breaking work was only published in the journal of his employer, the "Wheat Studies of the Food Research Institute", Kaldor was perhaps unaware of it, certainly he did not reference it. Kaldor noted that during backwardation, holding a physical position seems, at first glance, to be illogical, since it is clear from the futures market that prices are expected to fall. Why not simply buy later at a lower price, or buy a long-dated future rather than buy in the spot market? He introduced the term "convenience yield", i.e., the convenience or benefit derived from holding the physical commodity rather than a paper futures contract. This was measured as a percentage yield (as proposed by Working) which the holder of the physical asset implicitly receives to offset the decline in price. Often the theory of storage is initially credited to Kaldor (Fama and French 1987; Brennan 1958 and others). We believe that much belated credit is mainly due to Working, partly because he 'got there first', and partly because Working explicitly plots graphically the relationship between spread and inventory, whereas Kaldor only discusses the relationship in general qualitative terms.

Brennan (1958) contributed further to the development of the theory of storage. He took empirical data for a number of agricultural commodities (eggs, cheese, butter, wheat and oats) over a period of years, and showed that the Working curve was observed in many markets. Whereas Working had framed the theory in terms of yearly observations, Brennan noted that it held at all times, using monthly observations.

Further evidence to support the Working curve has been found over the years in a range of commodities, such as heating oil, copper and lumber (Pindyck 1994), soybeans (Geman and Nguyen 2005) and crude oil and natural gas (Geman and Ohana 2009). Convenience yield is usually said not to exist in the case of electricity, due to its non-storability. However, in the special case of the Scandinavian Nordpool electricity market, unusual because a large proportion of its electricity is generated from hydroelectric dams, water stored in the dams serves as an inventory of electricity (Botterud, Kristiansen, and Ilic 2010).

Development of the Theory of Storage –Inventory and Volatility

The 2nd branch of the theory of storage, described in our *Prediction 2* was again first discussed by Working in his seminal 1933 paper. However, it took some years before further empirical work was done on the relationship between volatility and inventory.

Fama and French (1988) test five base metals (aluminium, copper, lead, tin and zinc) traded on the London Metal Exchange (LME) from 1972 to 1983, as well as 3 precious metals, gold, platinum and silver. In the absence of formal inventory data, they use interest-adjusted spread as a proxy for inventory. In the case of the base metals, they find that spot price volatility rises as inventory decreases. Gold inventories are always high (central banks and other reserves hold inventory, although the willingness of the owners to sell is sometimes in doubt), so spreads are little-varying and therefore offer little forecast power for price volatility.

Other studies of the relationship between volatility and inventory in the case of metals include:

- Ng and Pirrong (1994) study four base metals traded on the London Metal Exchange (LME): aluminium, copper, lead and zinc, from 1986-1992. They do not have access to inventory information, so use the adjusted spread as a proxy. They find, as predicted, a strong relationship between spread and spot price volatility.
- Brunetti and Gilbert (1995) examine 6 LME-traded base metals and find that low inventory levels (adjusted for worldwide consumption) are correlated with periods of high spot price volatility.

Data and the Units of Inventory

The relationship between price and inventory is usually represented in terms of convenience yield. The convenience yield, usually denoted $y(t, T)$, the benefit accruing to a holder of a physical commodity between times t and T that is not enjoyed by the owner of a futures contract, can be derived from the spot-futures relationship in Equation (1), see Appendix A for details.

$$F(t, T) = S(t)e^{[r(t, T) + c(t, T) - y(t, T)](T - t)} \quad (1)$$

We therefore need a historical database of prices, both spot and futures for the 6 base metals, as well as of $r(t, T)$, the cost of financing over (t, T) in the currency in which the commodity is traded, and $c(t, T)$, storage costs per unit of inventory from time t to T . Naturally we also need a historical database recording the quantity of each metal held in inventory.

Price Database

In many commodity markets, liquidity exists mainly in the futures market while spot markets are thinly traded, if at all. In these cases, it is common to use the first nearby future price as a proxy for the spot price. Still, futures prices often suffer from technicalities around rollover dates and thin liquidity as delivery date approaches. Fortunately, structural reasons related to the nature of trading imply that metal spot and futures prices reported by the LME are reliable and can be used directly (Fama and French 1988). Since the theory of storage is mainly concerned with relatively short-term effects caused by abundant or low inventory, we study the ‘short’ end of the futures curve using the spot and 3 month prices published by the LME.

Our price database from the LME covers the period January 1983 to June 2011, except in the case of tin and zinc, when we start in January 1990 due to absence of inventory data or suspension of trading during the earlier period. All prices were initially quoted in British Pounds during the early years of our study period, later transferring into US\$, so when necessary we convert to US\$ using the prevailing spot £/\$ spot rates.

Inventory Database

We mainly use inventory data as reported daily by the LME, being the total metal inventory held in the large number of LME-appointed warehouses worldwide. All inventory figures are in metric tonnes. We also compiled additional inventory data:

- Aluminium and Copper also trade (or were traded) for some years on the COMEX exchange in New York, although the main world market remains the LME. COMEX publishes its own daily inventory data for its warehouses.
- The US Geographical Survey (USGS) publishes its estimates of annual, year-end US commercial stocks for all 6 base metals. However, in some cases, there is risk of double-counting inventory held in US-based LME warehouses.

- In recent years, the Shanghai Futures Exchange, SHFE, has begun trading aluminium, copper and zinc and publishes its own daily warehouse figures from 2003 onwards (2007 for zinc).
- In the case of Aluminium, the International Aluminium Institute publishes monthly surveys of worldwide total aluminium commercial and government stocks, and explicitly excludes LME warehouses.

World Consumption Database

In order to compare inventory with increasing worldwide consumption, we use an annual series of worldwide metal consumption (this includes both primary and secondary – recycled – materials), from World Metal Statistics.

Storage Costs

Historical storage costs are unavailable for the LME warehouses. At the time of writing, 2011, costs for all six of the base metals, at all warehouses worldwide, were in the range \$0.36 - \$0.46 per tonne per day (LME 2011b), summarized in Table 1. These costs are typically set once per year, with minimal variations from year to year. The costs correspond to annual storage costs ranging from <1% to 5% p.a. of the value of the metal, i.e. low numbers compared to the situation of crude oil or natural gas. Warehouse costs are highly consistent across the globe (see the low standard deviations of cost across all relevant warehouses in Table 1). There are few warehouse operators, and in recent years they have mainly been taken over by the major banks and commodity trading houses, a situation some claim allows unfair advantage and the possibility of a single player to ‘corner’ the market (we will examine these claims later), this is certainly at least a source of asymmetry of information. We estimate historical warehousing costs by deflating the 2011 cost by the US CPI Index.

	Aluminium	Copper	Lead	Nickel	Tin	Zinc
Average Cost, 2011 (US\$ per tonne per day)	0.408	0.367	0.362	0.453	0.422	0.375
Standard Deviation across Accepting Warehouses (US\$ per tonne per day)	0.0013	0.0006	0.0013	0.0013	0.0015	0.001

Table 1 : Average LME Warehouse Daily Storage Cost, 2011 (\$US Per Tonne Per Day)

Other Data

For ' r ', the cost of financing, we use the relevant constant maturity US treasury rates published by the US Federal reserve and made available by the reliable 'FRED' service.

Data Processing

We take monthly arithmetic averages over all trading days for inventory. For spread, we first make the computations at a daily frequency then take the monthly arithmetic average. Monthly volatility is calculated as the annualized standard deviation of daily log-returns observed during the month.

Choice of Units for Inventory

Although inventory is typically published in physical units (tonnes in the case of metals, barrels for oil, etc.), if we plot the LME inventory of the 6 metals over the study period (Figure 3), we see that the inventory for Aluminium dwarfs all others.

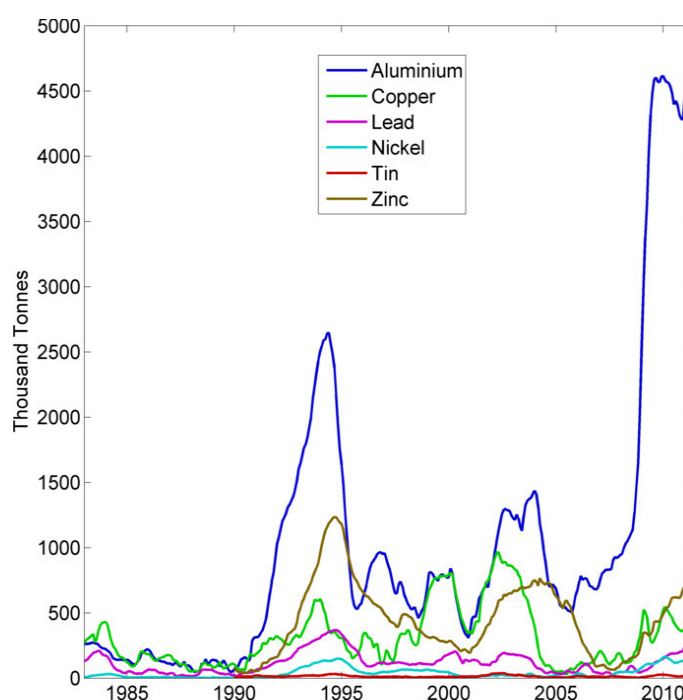


Figure 3 – LME Inventory in Thousand Tonnes for the 6 Base Metals over the Study Period

Given the large rise in worldwide consumption of each metal over the years (Figure 4), we opt to express inventory instead using the gauge of *days of worldwide consumption*, i.e., we divide inventory by annual consumption and represent it in days. Figure 5 shows LME inventory in this representation. We can now easily compare each metal and see trends

across the decades. We observe that inventory of each metal has tended to vary between circa 2 and 50-60 days of consumption, with notable peaks in 1994, 2003 and 2010. It is interesting to note that the inventory builds begin contemporaneously with a US recession, as in 1990, 2001 and 2008, but take some time to peak, showing that production responds only very slowly to reduced demand during such shocks. The shocks in demand are also visible as brief pauses in the upward consumption trend (Figure 4). We also note the metal inventories do not move in lockstep — at times we see inventory builds in some metals but not others. With the exception of zinc, inventories were universally low during the noted commodity price boom period of 2004-2008. Copper, the most important non-precious metal in terms of its share of world trade, has not seen inventories above 10 days' worth since 2004.

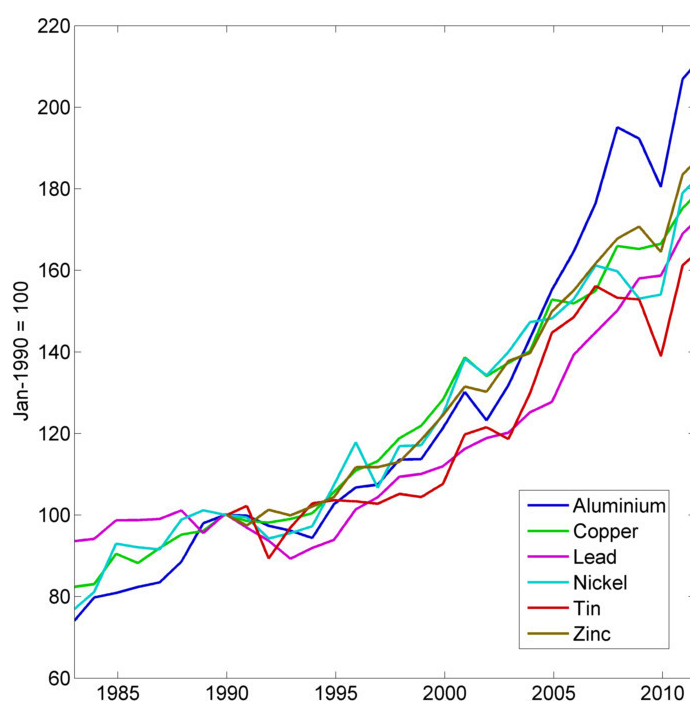


Figure 4 - Increasing Worldwide Consumption of each Base Metal over the Study Period (1990=100)

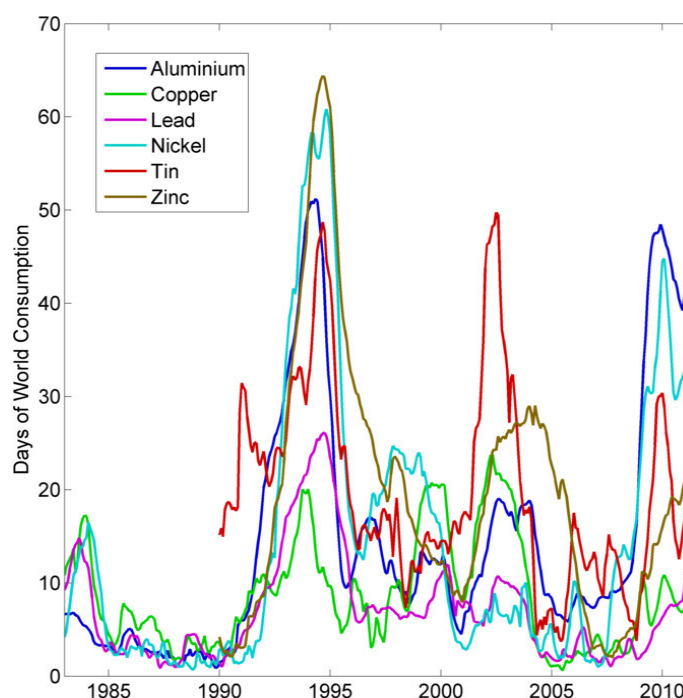


Figure 5 – Inventory Measured in Days of World Consumption

Results: The Relationship between Price and Inventory

As in Working (1933) we represent the relationship between spot and futures prices in terms of a spread, rather than looking at convenience yield. More precisely, we follow Geman and Ohana (2009) and others by calculating an ‘interest and storage adjusted spread’

$$\psi(t, T) = \frac{F(t, T) - S(t)e^{[r(t, T) + c(t, T)](T-t)}}{S(t)} \quad (2)$$

i.e., it is a ratio, representing the growth from the current spot price $S(t)$ to the futures price $F(t, T)$ for maturity $T > t$, adjusted for financing and storage costs. As a ratio, it can be thought of as a return relative to $S(t)$ from holding the physical commodity between t and T , and selling one future contract at date t for delivery at T .

In Figure 6, we plot, for each metal, a scattergram of monthly observations of the interest and storage adjusted spread (henceforth, ‘spread’) $\psi(t, T)$ against its contemporaneous inventory $i(t)$. A very clear and consistent picture emerges, relatively identical for each metal. We note the following features:

1. The vertical axis represents the extent to which the spot price is below the futures price, after funding and storage costs are removed. That is, a negative spread represents backwardation, with $\text{spot} > \text{futures}$.
2. The spread almost never exceeds 0, as expected; otherwise this would represent an arbitrage opportunity, obtained by purchasing the spot asset and simultaneously selling a 3 month future, paying funding and storage costs for 3 months, and delivering the metal to the futures counterparty after 3 months.
3. Whenever inventory exceeds around 30 days of worldwide consumption, we see a negligible spread, i.e., the futures curve is neither in strong backwardation nor contango.
4. When inventory falls below 10 days of worldwide consumption, an extreme spread often occurs, with spot 5% or even 10% above 3 month futures.
5. The curve is exactly as Working observed for wheat. However, he expressed inventory in terms of 'variation from the usual' whereas we measured absolute inventory in days of worldwide consumption.

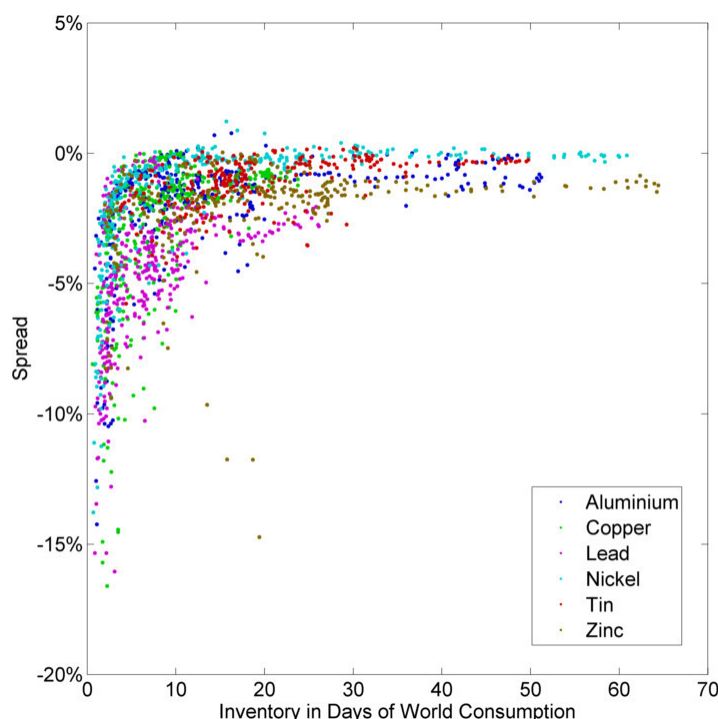


Figure 6 – Interest and Storage Adjusted Spread (Spot to 3 Month Future) vs. Inventory

Choice of Inventory

In order to determine whether LME inventories alone produce this strong result, or whether the inclusion of additional inventory data improve the fit further, we cannot perform a simple regression due to the non-linear nature of the Working curve observed. Instead, we use the Spearman (1904) rank correlation statistic, denoted ρ_s , which measures monotonic dependence whilst being robust to non-linearities. As with the more widely used Pearson correlation, which we denote ρ_p , a value of 0 indicates no relationship, and a value of 1 indicates perfect correlation. Our results are displayed in Table 2.

	Aluminium	Copper	Lead	Nickel	Tin	Zinc
LME	0.590	0.679	0.500	0.878	0.604	0.470
LME + COMEX	0.570	0.683	–	–	–	–
LME + SHFE	0.593	0.737	–	–	–	0.579
LME + COMEX + SHFE	0.578	0.731	–	–	–	0.579
LME + USGS	0.271	0.660	0.253	0.597	0.518	0.168
LME+IAI	0.100	–	–	–	–	–

Table 2 – Spearman Rank Correlations between Interest- and Storage-Adjusted Spread and Inventory, using Various Measures of Inventory

We interpret the results as follows. A strong relationship exists even when the sole LME inventories are considered (and typically the LME inventories make up the bulk of the world's total published inventories). The addition of COMEX inventories barely changes the correlation, possibly because the COMEX inventories are small compared to those in LME warehouses. SHFE inventories, initially small, are now growing to rival those of the LME. The addition of SHFE inventories significantly improves the relationship for copper and zinc and barely changes it for aluminium. This lends credence to the reliability of the SHFE inventory data, refuting those who claim that inventory reporting in China is highly opaque. The commercial inventory data (USGS and IAI) weaken the relationship. These cover inventory reported as 'on-hand' by individual companies, still in ports etc. We theorise that this inventory is available to individual market participants but *not to the industry as a whole*, and hence are not useful to the wider market, and therefore does not contribute to the market's perception of *available* inventory.

Stability of Relationship

In order to test whether the relationship is stable over the 28-year study period (1983 to 2011), we subdivide the study period into 4 equal sub-periods, and report the Spearman correlation separately for each sub-period (Table 3). We return to the LME-only inventory figure. A value of ‘–’ indicates the relevant metal was not traded during the sub-period for sufficient time for a meaningful analysis.

	Aluminium	Copper	Lead	Nickel	Tin	Zinc
1983-1989	0.872	0.919	0.931	0.837	–	–
1990-1996	0.060	0.767	0.470	0.778	0.585	0.470
1997-2003	0.110	0.790	0.160	0.809	0.812	0.319
2004-2011	0.627	0.914	0.578	0.850	0.507	0.284

Table 3 – Spearman Rank Correlations between Interest- and Storage-Adjusted Spread and Inventory, over Different Sub-Periods

We see that broadly, the relationship has remained solid over the entire period. There are few periods (e.g. Aluminium, 1990-1996 and 1997-2003) when the relationship is weak. Only in the case of tin and zinc is the relationship weaker in the most recent period, 2004-2011. Overall, we propose that the relationship holds as strongly now as it ever has.

We also tested whether representing inventory in days of worldwide consumption leads to a stronger relationship than simply representing inventory in tonnes. Again, we return to the LME-only inventory figure. Table 4 shows the results. Interestingly, measuring inventory in traditional tonnes gives in most cases a slightly better fit. This demonstrates that despite global consumption roughly doubling over the study period, the industry is now able to operate with the same absolute tonnage of inventory (indeed inventories, although substantially lower before 1990, have not risen greatly since 1990 in tonnes apart from the case of aluminium, see Figure 3). We hypothesize that with the rise over the years of ‘just-in-time’ stockholding techniques, and perhaps greater information flows about inventory size and location, the global metals industry is able to more efficiently allocate inventory to isolated shortages, preventing spot price spikes.

	Aluminium	Copper	Lead	Nickel	Tin	Zinc
Inventory in days of worldwide consumption	0.590	0.679	0.500	0.878	0.604	0.470
Inventory in tonnes	0.606	0.772	0.589	0.864	0.638	0.537

Table 4 – Spearman Rank Correlations between Interest- and Storage-Adjusted Spread and Inventory, using Different Measures for Inventory.

Results: The Relationship between Volatility and Inventory

We now turn to the relationship between volatility and inventory. We calculate a monthly volatility value for the spot and the 3 month futures prices for each metal by taking the standard deviation of the daily log-returns in the given month, and multiplying by $\sqrt{252}$ to obtain an annualised volatility.

We plot in Figure 7 below the relationship between spot price volatility and inventory. Although we see that broadly, spot price volatility increases with low inventory, the picture is muddy. Clearly other factors also cause occasional spikes in volatility, evidenced by the quantity of dots for several metals with high volatility despite high inventory.

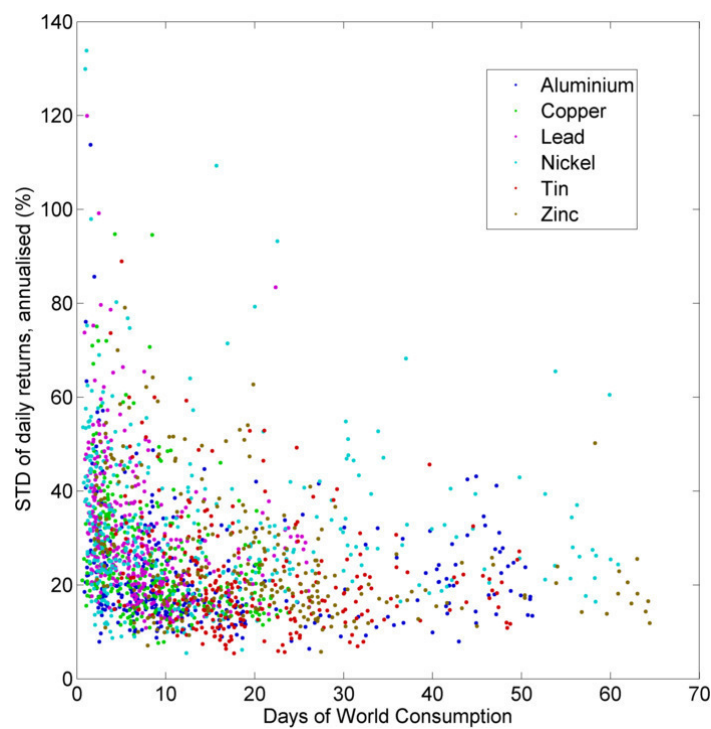


Figure 7 – Spot Volatility vs. Inventory

We now define a value we term ‘excess volatility’ σ_{excess} , representing the excess ratio of spot price volatility σ_{spot} over futures price volatility $\sigma_{futures}$, calculated as:

$$\sigma_{excess,t} = \frac{\sigma_{spot,t} - \sigma_{futures,t}}{\sigma_{futures,t}} \quad (3)$$

We design σ_{excess} to remove factors affecting long-term volatility, that could be expected to affect both σ_{spot} and $\sigma_{futures}$, and isolate only those short-term factors that affect only σ_{spot} .

If we now plot inventory (as above, LME inventory in days of worldwide consumption) against σ_{excess} , see Figure 8, we obtain a much clearer relationship.

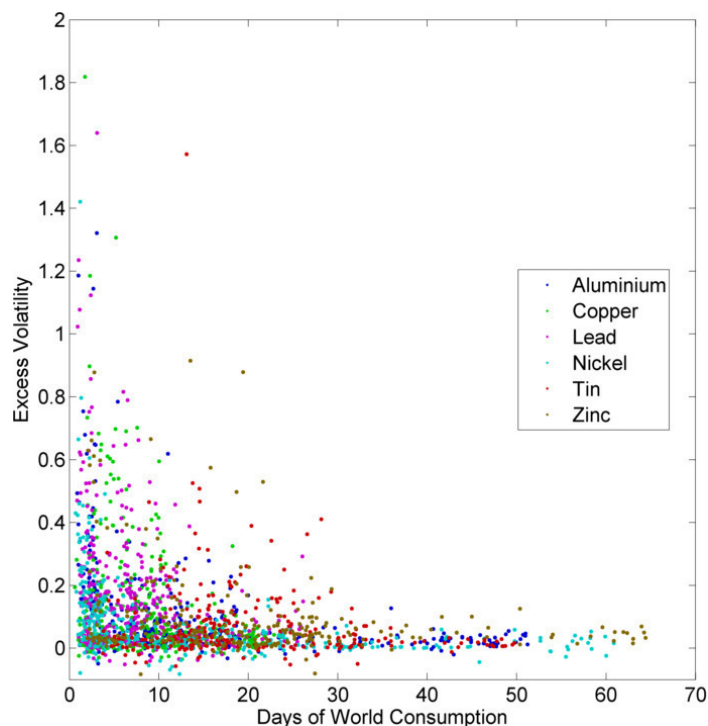


Figure 8 – Excess Volatility vs. Inventory

We interpret the graph as follows:

- σ_{spot} is almost never less than 3 month $\sigma_{futures}$ (i.e., σ_{excess} is almost never < 0). This supports the ‘Samuelson effect’ (Samuelson 1965), noted as early as Working (1933), that volatility rises towards maturity.
- When inventory is more than 30 days of world consumption, σ_{spot} and $\sigma_{futures}$ are almost identical. We would see this as “parallel shifts” of the futures curve at such times.
- When inventory is less than 10 days, σ_{spot} may rise to 0.2x (20%) or more above $\sigma_{futures}$. However, unlike the Working curve, this “excess volatility curve” does not have a rounded corner near the origin, i.e., there are times of low inventory when σ_{spot} does not exceed $\sigma_{futures}$ despite low inventory.

To test numerically whether this “excess volatility curve” relationship holds true for all metals, we display in Table 5 the Spearman correlation between volatility and inventory, both in the case of σ_{spot} and σ_{excess} . We observe, as expected, negative correlations in all cases. Similar to the most commonly used Pearson measure of correlation, the negative correlation indicates a high value for volatility corresponds to a low value for inventory. The relationship is stronger between inventory and σ_{spot} for some metals (copper, lead, tin, zinc) and between inventory and σ_{excess} in others (aluminium, nickel). Although the correlations are pronounced, they indicate a weaker relationship between volatility and inventory than for the strong spread-inventory relationship noted earlier.

	Aluminium	Copper	Lead	Nickel	Tin	Zinc
$\rho_S(\sigma_{spot}, inventory_{days})$	-0.253	-0.466	-0.469	-0.165	-0.244	-0.406
$\rho_S(\sigma_{excess}, inventory_{days})$	-0.482	-0.205	-0.208	-0.571	-0.078	-0.166

Table 5 – Spearman Rank Correlations between Volatility and Inventory in Days.

Finally, we again check whether inventory is best expressed in number of days or tonnes, see Table 6. For every metal, using raw tonnes weakens the relationship between σ_{spot} and inventory, but strengthens the relationship between σ_{excess} and inventory. How do we interpret this? For spot volatility (which may capture both rises in short term volatility, and rises in volatility across the entire futures curve), the inventory in days is most important, i.e., increasing inventories have been required over time commensurate with increased consumption in order to dampen overall volatility. However, excess volatility is more susceptible to absolute inventory in tonnes, i.e., it has adapted over the years to accept the smaller inventories held per unit of consumption.

	Aluminium	Copper	Lead	Nickel	Tin	Zinc
$\rho_S(\sigma_{spot}, inventory_{tonnes})$	-0.177	-0.384	-	-	-	-
			0.376	0.073	0.029	0.274
$\rho_S(\sigma_{excess}, inventory_{tonnes})$	-0.494	-0.333	-	-	-	-
$\sigma_{excess}, inventory_{tonnes})$			0.313	0.593	0.261	0.298

Table 6 – Spearman Rank Correlations between Volatility and Inventory in Tonnes.

Applications

We see several applications for these results, detailed below.

Forecasting

Trajectories of inventory, as demonstrated in Figures 3 and 5, appear to be mean-reverting, and are certainly not random walks. They display high levels of autocorrelation in their changes, i.e., inventory rises or falls continuously for many weeks before reverting. Over the short term of several weeks, inventory changes are therefore fairly predictable. Given the strong influence of inventory over both the spot-futures price spread and various measures of volatility, a model for inventory could thereby predict likely spreads and volatilities out to an horizon of perhaps 1 or 2 months. We propose that the use of stochastic differential equations with autocorrelation of returns and mean-reversion of levels would be a good starting point for modelling base metal inventories.

Investigating Market Abnormalities

The seminal paper of Black and Scholes (1973) showed that given several parameters, namely the price of an underlying asset and its volatility, the risk free interest rate, and a duration, the value of an option contingent on that asset could be expressed as a simple closed-form formula. It was soon observed that given an option price already quoted in the market, and the other parameters excluding volatility, an *implied volatility* could be calculated, namely the (unique) volatility that would give that option price had the Black-Scholes option pricing formula been used. This *implied volatility* can in turn be used to price more complex options, or it can be used to confirm that the various options on an underlying are neither under- or over-priced.

We propose a similar approach; we derive *inventory implied spot price* and *inventory implied spot volatility* for a commodity. We can compare these with observed values of spot price and spot price volatility. If the implied and market values are in agreement, we can conclude that the market is functioning “normally” with respect to inventory, i.e., the inventory in warehouses is considered “useful” to the market in the normal way. If inventory has been “cornered” by a market participant, or another market abnormality implies that inventory is not “available” to the wider market, we would expect to see elevated values for spot price and spot price volatility.

Inventory Implied Spot Price

We fit a functional form between spread and inventory, as plotted in Figure 6. We choose for the functional form:

$$\psi(t, T) = Ae^{Bi(t)} + C \quad (4)$$

where we expect $A < 0$, $B < 0$, $C \approx 0$ with $C \leq 0$ reflecting no cash-and-carry arbitrage opportunities, and $T = t + 3$ months as in the rest of our analysis. Rather than calibrate using simple least-square methodology, which fits the curve based on the bulk of the observations and are of moderate inventory values in each case, we employ a variation of least-squares described in Appendix B.

Others have fitted different functional forms to the relationship between inventory and spread to convert it to a linear one. Geman and Nguyen (2005) used

$$K \frac{1}{i(t)}, K < 0 \quad (5)$$

for soybeans, where scarcity is defined as inverse inventory, and obtain conclusive results.

We displayed the results for each metal in Table 7, and the fitted curves in Figure 9. We note that the fitted curves take a similar form for each metal, although copper displays a ‘tighter’ curve (indicating tolerance of lower inventory values than for other metals) and tin displays little curvature. In the case of tin, we have never had a case of extremely low inventories, so there are no ‘low inventory’ values to fit and the fitted line does not curve sharply downwards.

Now we have a prediction for the spread $\hat{\psi}(t, T)$; given $i_{days}(t)$, we can invert equation (2), and obtain a prediction for the spot price $\hat{S}(t)$.

	Aluminium	Copper	Lead	Nickel	Tin	Zinc
Monthly samples fitted	342	342	342	342	258	258
A	-0.0160	-0.0814	-0.2357	-0.2350	-0.0276	-0.0609
B	-0.0506	-0.2081	-1.0178	-0.9225	-0.0556	-0.3324
C	-0.0097	-0.0077	-0.0343	-0.0054	-0.0007	-0.0171

Table 7 – Fitted Results Approximating the Spread as a Function of Inventory (measured in days)

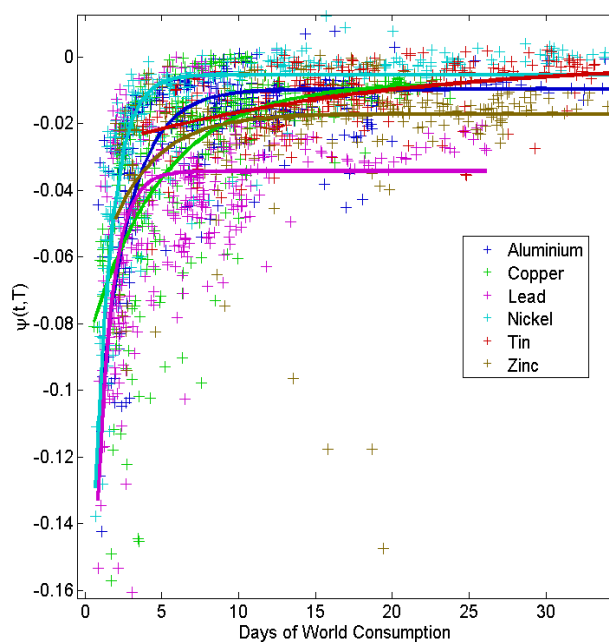


Figure 9 – Fitted Working Curves (Spread vs. Inventory)

Inventory Implied Spot Volatility

Noting from Figure 8 the similar form of the relationship between inventory and excess volatility σ_{excess} (defined in equation(3)), we repeat the above exercise, fitting a curve of the same form:

$$\sigma_{excess}(t) = Ae^{Bi(t)} + C \quad (6)$$

Where again now expect $A > 0$, $B < 0$, $C \approx 0$ but not necessarily $C > 0$ because there is no economic reason to anticipate σ_{spot} to be always higher than futures. A fitted graph is displayed in Figure 10 and the fitted values in Table 8. The fitted curves all take the same form, although again the tin ‘curve’ has little curvature due to the lack of low-inventory historical values for tin. We also see surprisingly little curvature for copper.

	Aluminium	Copper	Lead	Nickel	Tin	Zinc
Weekly samples to fit	342	342	342	342	258	258
A	0.6882	0.1984	3.8888	0.4979	0.0627	0.6534
B	-0.4540	-0.0636	-2.0678	-0.5839	-0.0109	-0.1087
C	0.0422	0.0047	0.1351	0.0237	0.0080	0.0189

**Table 8 - Fitted Results Approximating the ‘Excess Volatility’
as a Function of Inventory (measured in days)**

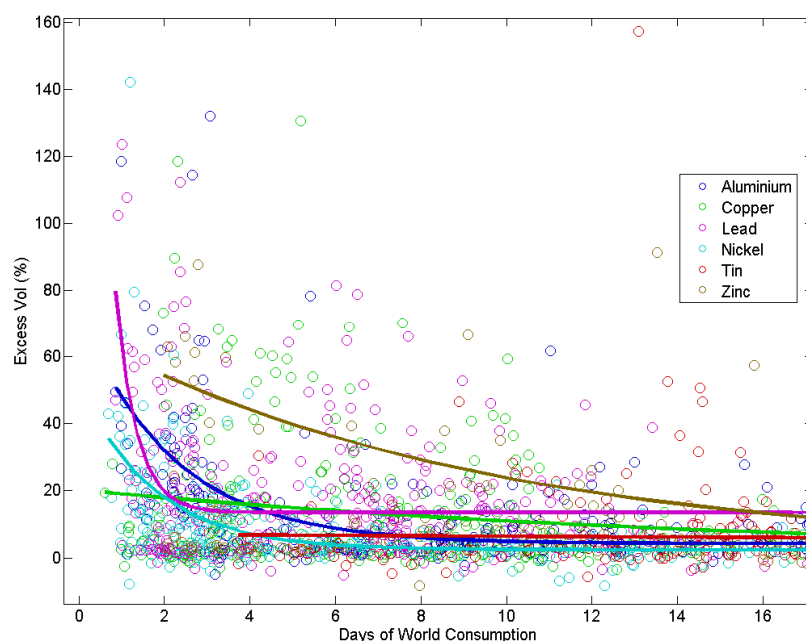


Figure 10 – Fitted Excess Volatility Curves (σ_{excess} vs. Inventory)

Similarly to the case for inventory-implied spot price, given $i_{days}(t)$, we have now a prediction for the excess volatility (denoted $\hat{\sigma}_{excess}(t)$); we can invert equation (3) and obtain a prediction for spot volatility $\hat{\sigma}_{spot}(t)$.

Using Inventory-Implied Spot Price and Volatility

We can now compare the inventory implied values for spot price and spot volatility with those observed in the market. This tells us whether the market is behaving in the ‘usual’ way with respect to the observed level of inventories. If either the empirical spot price or the empirical spot volatility exceeds that predicted, the market is acting as if the observed inventory is unavailable or only partially available. This would then tend to imply market manipulation or a corner by one inventory owner of the market. There have been many allegations of such activity in the period 2010-2011 (MSNBC.com 2011; Bloomberg 2011 etc.) We plot therefore in Figure 11 and Figure 12 the ratios:

$$S_{ratio}(t) = \frac{S(t)}{\hat{S}(t)} \quad (7)$$

$$\sigma_{ratio}(t) = \frac{\sigma_{spot}(t)}{\hat{\sigma}_{spot}(t)} \quad (8)$$

for the cases of both Aluminium and Copper. In both cases, the lines hover close to 1.0 in recent years, with no upward spikes. Any discrepancy between the empirical spot values (price, volatility) and the inventory-implied values seem to have occurred prior to around 1997 and substantially disappeared since then. The graphs for the remaining four base metals (not displayed) are substantially similar. We can then conclude that there is no evidence from spot prices and volatilities that one or more major players are manipulating the base metals by keeping inventory from the market.

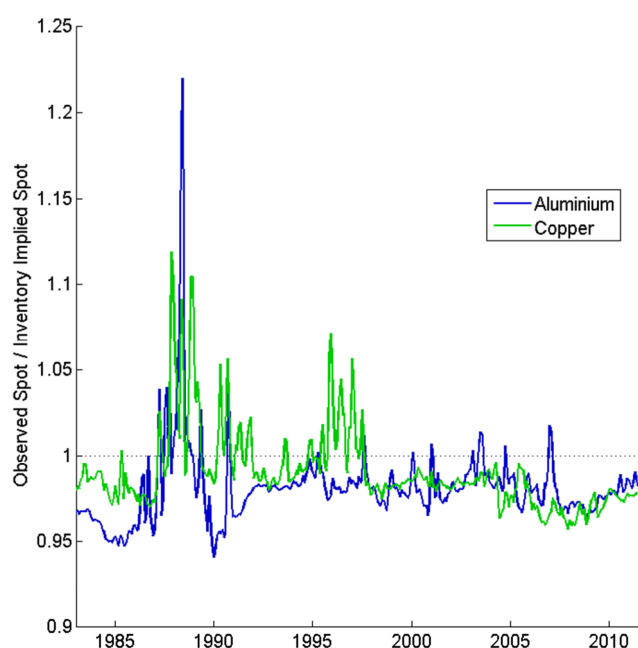


Figure 11 – Ratio of Empirical Spot Price and Inventory-Implied Spot Price over the Study Period

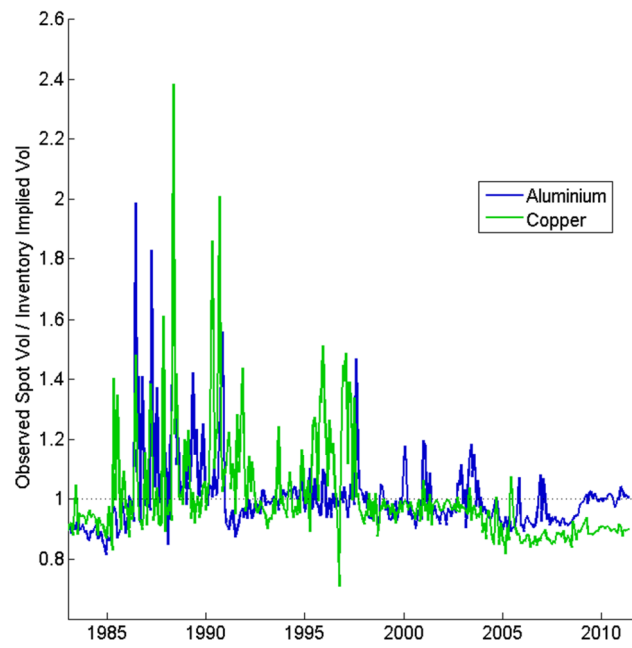


Figure 12 – Ratio of Empirical Spot Volatility and Inventory-Implied Spot Volatility over the Study Period

Conclusion

Working's theory of storage, and its two key predictions related to price and volatility, originally formulated for wheat, and initially validated in other agricultural markets, has been shown here to be strongly validated in the case of the six base metals traded on the LME.

We find a strong non-linear relationship between the adjusted- spread of the forward curve (based on a ratio between spot and futures prices) and inventory. In addition, we have shown that the relationship between spot volatility and inventory is strengthened further by introducing the concept of 'excess volatility'. This is analogous to the spread, in that it represents the excess of spot volatility over futures volatility.

We have shown that the inventory figures from LME warehouses alone suffice to generate the two strong relationships above. The addition of Chinese inventories figures at the SHFE slightly strengthens the relationship further, highlighting the increasing importance of China in metal demand and trade, and refuting some suggestions that Chinese inventory data cannot be trusted. The addition of inventory figures from other exchanges and trade organisations does not improve the relationship, highlighting further that only the LME and the SHFE need be followed, for now at least.

Finally, based on our novel concepts of inventory-implied spot price and inventory-implied spot volatility, we seen no evidence that the recent allegations of major market players withholding inventory is substantiated, to the extent that LME prices are behaving as if the full inventory figures are available to the market.

Appendix A – Calculation of Convenience Yield and Interest-Adjusted Spread

Formally, the relationship between futures and spot prices is usually expressed as:

$$F(t, T) = S(t)e^{[r(t, T) + c(t, T) - y(t, T)](T - t)} \quad (\text{A.1})$$

where

- $F(t, T)$ is the futures price of a commodity for delivery at time T , as observed at time t
- $S(t)$ is the spot price of the commodity observed at time t
- $r(t, T)$ is the annual cost of financing the futures position from time t to T
- $c(t, T)$ is the annual cost of storage of the physical commodity from time t to T , also expressed as a rate
- $y(t, T)$ is the annual ‘convenience yield’ enjoyed by the holder of the stored commodity from time t to T , and is calculated to satisfy the equality, rather than observed directly.

We can understand the above relationship as follows. The convenience yield from holding a spot contract from t to T is termed the ‘basis’, calculated, for example by Fama and French (1987), as

$$\text{basis}(t, T) = \frac{F(t, T) - S(t)}{S(t)} \quad (\text{A.2})$$

If we taking into account the cost of financing and storing a long physical position for duration $(T - t)$ we derive a term which has been called the ‘interest and storage- adjusted spread’, which we term simply ‘spread’

$$\psi(t, T) = \frac{F(t, T) - S(t)e^{[r(t, T) + c(t, T)](T - t)}}{S(t)} \quad (\text{A.3})$$

By expressing (A.1) and (A.3) in a discretely compounded form, we can more easily see the relationship between spread and convenience yield:

$$F(t, T) = S(t) \left(1 + [r(t, T) + c(t, T) - y(t, T)](T - t) \right) \quad (\text{A.4})$$

$$F(t, T) - S(t) = S(t) [r(t, T) + c(t, T) - y(t, T)](T - t) \quad (\text{A.5})$$

$$\frac{F(t, T) - S(t)}{S(t)} = [r(t, T) + c(t, T) - y(t, T)](T - t) \quad (\text{A.6})$$

$$y(t, T)(T - t) = [r(t, T) + c(t, T)](T - t) - \frac{F(t, T) - S(t)}{S(t)} \quad (\text{A.7})$$

$$y(t, T) = r(t, T) + c(t, T) - \frac{\frac{F(t, T) - S(t)}{S(t)}}{T - t} \quad (\text{A.8})$$

and

$$\psi(t, T) = \frac{F(t, T) - S(t) \left(1 + [r(t, T) + c(t, T)](T - t) \right)}{S(t)} \quad (\text{A.9})$$

$$= \frac{F(t, T) - S(t)}{S(t)} - \frac{S(t) [r(t, T) + c(t, T)](T - t)}{S(t)} \quad (\text{A.10})$$

$$= \frac{F(t, T) - S(t)}{S(t)} - (r(t, T) + c(t, T))(T - t) \quad (\text{A.11})$$

$$\frac{\psi(t, T)}{T - t} = \frac{\frac{F(t, T) - S(t)}{S(t)}}{T - t} - r(t, T) - c(t, T) \quad (\text{A.12})$$

$$= -y(t, T) \quad (\text{A.13})$$

From (A.13), it is clear that convenience yield is nothing more than an annualised version of the spread, but expressed with opposite sign.

Appendix B – Exponential Curve Fitting Procedure

To calibrate an exponential curve fitting the shape of the empirical Working curve (Figure 9) or excess volatility curve (Figure 10) we found that the following procedure gives a good visual fit:

- Define $j(t)$ as the log of inventory (measured in days), $j(t) = \ln(i_{days}(t))$
- Identify $n+1$ points k_m , $m \in \{0, \dots, n\}$ linearly dividing $j(t)$ into n equal 'bins', and convert back into units of inventory from log-inventory. This prioritizes the low- and moderate- inventory end of the relevant curve over the widely-spaced, high inventory values, helping to fit a close curve at the left-hand side. We chose $n = 40$:

$$k_m = e^{\min_{\tau=1}^t(j(\tau)) + \frac{m}{n} \left(\max_{\tau=1}^t(j(\tau)) - \min_{\tau=1}^t(j(\tau)) \right)} \quad (\text{B.1})$$

- For each interval k_m to k_{m+1} , identify the mean inventory figure in the 'bin':

$$\bar{i}_m = \text{mean}(i(t) | k_m \leq i(t) < k_{m+1}) \quad , m \in \{0, \dots, n-1\} \quad (\text{B.2})$$

- Finally, fit an exponential curve through the mean values in each bin \bar{i}_m , minimizing the RMS error between the fitted curve values and the mean values in each bin.

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Chapter 3

Extending the Theory of Storage: From Inventory to Reserve Capacity in Energy Markets

Abstract

The theory of storage, originally proposed by Working in 1933, noted that both the price and price volatility of a commodity were strongly influenced by the quantity held in inventory. Empirical confirmation has been obtained for a wide range of storable commodities. We show that the theory of storage can be expanded to electricity by identifying ‘margin reserves’ as a close analogue for inventory. We also demonstrate that reserve capacity can be used as a fundamental predictive factor for crude oil prices.

Introduction

The Theory of Storage

The theory of storage was developed by Working in the 1930's although his later summary of the theory is more widely cited (Working 1949). Prior to this theory, the variations in agricultural futures prices throughout the year had not been satisfactorily explained. Working showed that prices responded to variations in the amount of the commodity (in his case, wheat) held in storage (often termed 'inventory'¹). In particular, he studied the total quantity remaining in inventory at the end of one 'crop year', just prior to the new harvest. He noted two major effects:

1. During periods of 'scarcity' (i.e., when inventory was lower than average), spot prices rise sharply compared to Futures prices. Conversely, during periods of abundance and high inventories, spot prices are not particularly high.
2. A similar relationship exists with volatility, namely (spot price) volatility becomes elevated during times of scarcity.

Further conceptual development of Working's theory of storage was made by Kaldor (1939). Like Keynes (1930) he noted that during periods of low inventory, the level of spot prices above Futures prices meant that holders of inventory benefited from the inventory they held. Kaldor introduced the term 'convenience yield' to describe this situation (and the shape of the forward curve).

Telser (1958) and Brennan (1958) conducted further empirical testing, finding that the theory held for other agricultural commodities, including cotton and oats. The applicability of the theory of storage to non-agricultural commodities began with Fama and French (1988); Ng and Pirrong (1994) in the case of metals and Pindyck (1994) for heating oil. More recently, further empirical support has been noted in soybeans (Geman and Nguyen 2005), natural gas and crude oil (Geman and Ohana 2009) and six industrial metals (Geman and Smith, 2012).

Electricity as a Non-Storable Commodity

With most commodities well described by the theory of storage, a problem arises with non-storable commodities, with electricity being the major example. Shipping services,

¹ We avoid the alternative term 'stocks' for inventory to avoid any possible confusion with equity markets.

sometimes grouped with commodities and not covered here may be viewed as an extended type of non-storable commodity.

Deregulation of electricity markets began in the 1980s and accelerated in the 1990s. What used to be produced by a single government monopoly in each country was now generated by competing private utilities. Markets to facilitate the trading of electricity were created, and were incrementally refined as problems in market design were observed (most notably during the Californian electricity crisis of 2000-2001); electricity markets have been heavily studied by academics and practitioners ever since (Eydeland & Geman 1998; Eydeland & Wolyniec 2002; Harris, 2006).

Electricity non-storability arises because of its nature as a flow of electrons. With current technologies, the only economically feasible way of storing electricity is performed either (1) by releasing water through hydroelectric dams at a variable rate, or (2) using pumped-storage power stations, whereby water is repeatedly pumped up a large vertical distance (typically a mountain) and allowed to fall again, through a turbine, to recover that electricity (approximately 80% of the energy input). Electricity markets are usually isolated by country or geographical area (although they are becoming more interconnected). Only a small minority of electricity markets use significant hydro-power (notably Brazil and the 'Nordpool' Scandinavian market). Elsewhere, pumped storage and hydro combined typically make up less than 10% of total generating capacity, (UK : 1%, DECC (2012)). Except for those rare markets with large hydro components like Brazil, we can justifiably state that electricity is a non-storable commodity.

Margin Reserves as a Substitute for Inventory

As noted above, holding inventory permits the holder to immediately cover an unexpected rise in demand of a storable commodity. In the case of electricity, although we have strictly speaking no inventory, *margin reserves* exist most of the time to account for abrupt changes in demand. By definition, they represent the amount of unused available capability of an electric power system (at peak load). Spinning reserves correspond to those plants that can be started in 10 minutes, non-spinning reserves in 30 minutes. We will alternatively define these generators as *reserve capacity*². Note that reserve capacity is also

² In electricity markets the two terms 'margin reserves' and 'reserve capacity' describe the available production capacity above current levels. In crude oil markets, which we examine later, the term 'spare capacity' is more common.

the standard terminology used to represent the number of minutes a fully charged battery can discharge energy (at a given flow rate) until it drops.

Methodology and Data

To examine the relationship between reserve capacity and electricity prices, we need to measure the reserve capacity existing in an electricity market at a given time and the price of electricity in the market at the same time. We chose the UK electricity market as our example, because of (a) its maturity as one of the longest-running and largest electricity markets and (b) the availability of a large amount of data.

The UK electricity market splits each day into 48 equal settlement periods of 30 minutes, with period 1 being 0h00 to 0h30, and so on (Elexon, 2009a).

Notation

We denote a sample of half-hourly data X from period i on day j as $X_{i,j}$. We denote a sample of daily data Y on date j as Y_j . We abbreviate $\max_i(X_{i,j})$ – i.e., the maximum value for X during the whole of day j – as $X_{\max,j}$, with corresponding abbreviations for min (minimum) and stdev (standard deviation) etc.

Reserve Capacity Data

The UK electricity grid operator, National Grid Plc., publishes daily several data, which we use to determine the reserve capacity available on a given day. We focus on the semi- hourly period in each day with the lowest reserve capacity, to obtain a wide range of values (e.g., winter weekdays around 5pm typically have very low reserve capacity, whereas summer weekends, even at the period of lowest reserve capacity, typically have very high reserve capacity). We use the following data:

- Daily forecasts are made by the grid operator of daily peak demand $D_{\max,j}^{\text{forecast}}$, daily generator capacity C_j^{forecast} , assumed to be constant throughout the day, and the difference (reserve capacity, $RC_{\min,j}^{\text{forecast}} = C_j^{\text{forecast}} - D_{\max,j}^{\text{forecast}}$) for each of the days 2 to 14 days ahead of the forecast day, available at <http://www.nationalgrid.com/uk/Electricity/Data/reserve/bmrs/daily/> We use the

nearest daily forecast available to a given day, usually the 2-day ahead forecast, but sometimes due to data gaps, the 3 or 4- day ahead forecast.

- Ex-post half-hourly demand figures $D_{\min,j}^{\text{outturn}}$ are published shortly after at the end of each day at <http://www.nationalgrid.com/uk/Electricity/Data/Demand+Data/>

Using these data and due to the lack of published outturn capacity (i.e. observed *ex-post*), the best estimate we can construct of the minimum reserve capacity on a given day is:

$$RC_{\min,j}^{\text{outturn}} = C_j^{\text{forecast}} - D_{\max,j}^{\text{outturn}} \quad (1)$$

Demand data have been published since 1 April 2001 to the date of analysis, 29 February 2012; however capacity forecasts are only available from 12 January 2006 onwards. Hence our period of analysis goes from 12 January 2006 to 29 February 2012.

Price Data

Electricity in the UK is generated by *generators* and sold to *suppliers*. A large proportion of electricity is traded in medium- term transactions (the ‘forward and futures market’, trading from 24 hours to several years forward) and in short-term bilateral trades (up to one hour before delivery of the electricity). However, due to the variations in demand or supply at the last minute, any shortfall or excess (*‘imbalance’*) is adjusted using the *balancing mechanism*. In this system, generators owning power stations (*‘generation units’*) bid for the right to produce more or less electricity than contracted. The cheapest bids are selected to balance the system. A complex calculation is then used to calculate the *System Buy Price* and *System Sell Price* (Elexon 2009b). Depending on whether the market was in shortfall or excess before the balancing mechanism ran, one of these is then selected to determine the *System Price*. It is this price, and the corresponding trades, that we study here.

This system price $S_{i,j}$ can be considered as the marginal price of electricity during the half-hour settlement period. This price is quoted in Sterling pounds per megawatt-hour of electricity (£/MWh). The price is highly volatile, varying both across the year (electricity demand in the UK peaks during winter, due to heating requirements) and across the day. Overnight prices of around 10 £/MWh were common in the early 2000s, whereas 30 £/MWh is more common now. In the evening peak, usually around period 36 (530pm to 6pm), prices

frequently rise to 100 £/MWh or more during winter, and prices of more than 500 £/MWh have been observed during spikes.

System prices are downloaded from Datastream, and are sourced from the APX Power market where the balancing mechanism trades are executed. Weekday prices are available from 27 March 2001 onwards.

Volatility

Since the theory of storage identifies a strong relationship between price volatility and inventory, we compute volatility as the annualized standard deviation of the daily average price using a rolling window of 5 days.

Examining the Origin of the Price – Reserve Capacity Relationship

In all electricity markets, *generation units* (power stations) of different types cost different prices to run, and hence charge varying amounts for their electricity. They also differ in *schedulability* (the ability to be rapidly turned on and off according to demand) and *predictability*, the degree to which the output can be predicted ahead of time. ‘Baseload’ generators such as nuclear and coal produce relatively constant quantities, because of their low fuel cost, and because their outputs cannot be rapidly changed (it takes several hours to bring a coal fired power station up to its desired output, and even longer for nuclear power stations). Renewable generation technologies with low predictability (notably, wind) also supply baseload power whenever they are available, because of their low running costs. Such renewable generators have no economic reason to be turned off (their ‘fuel’ is free and their substantial construction costs must be recouped), so owners of these generators must simply accept whatever price prevails in the market.

More schedulable and predictable electricity technologies include gas (using the efficient ‘*combined cycle gas turbines*’, CCGT for short) and hydroelectric power. The outputs of these can both be adjusted in a matter of minutes. For this reason, they are more likely to be used during the daytime when demand is higher, and turned off at night. In the case of gas, this saves the relatively expensive fuel, and in the case of hydroelectricity, this is because the stored water is limited to the size of the reservoir and best used during the day when market prices are higher.

Finally, we come to times of peak demand. Typically for the UK, these occur on cold winter days, mainly during the evening period of 5pm to around 6.30pm, when domestic consumers are most likely to increase the heating in their houses and use their cookers after a day at work. During these times, so called ‘peaker’ power stations run. They may only run for a few dozen hours per year and must recoup a large fixed investment by charging a high price. Peaker generating units include oil fired generators and ‘OCGT’ (open cycle gas turbine) generators. Pumped storage is also a peaker technology, and is the ultimate technology in terms of schedulability, indeed it is often used for ‘TV pickup’ to meet electricity demand spikes during the advertising breaks of popular TV programmes, when many people simultaneously boil kettles to make tea or coffee!

As we describe in detail in the results section, we observe a strong relationship between reserve capacity and price. As the amount of demand gets larger, the corresponding ‘bids’ for electricity from more expensive units form the *power stack*. Figure 1 shows a hypothetical but typical power stack.

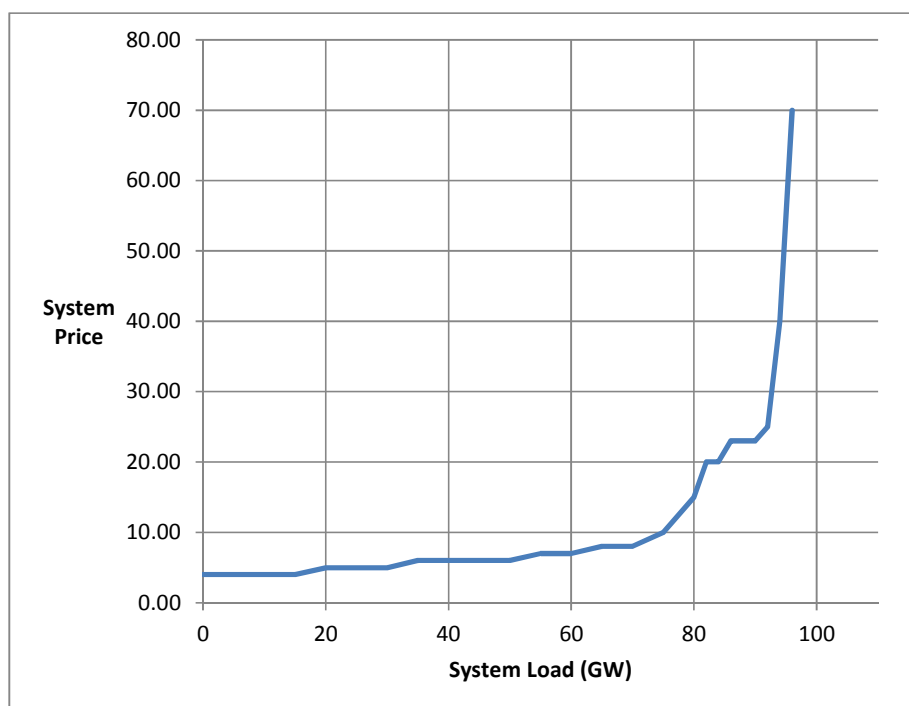


Figure 1 – A Prototypical Power Stack Showing the Sharp Rise in System Prices beyond some Demand Level

We also test whether prices rise during low reserve capacity even within a given generation type (e.g., CCGT gas)³. To test this, we disaggregate the power stack by generation type, as follows:

1. For each day, we identify the period with the lowest reserve capacity $RC_{min,j}^{outturn}$.
2. We extract the full bid stack of matched prices, published on the ‘Balancing Mechanism Reporting’ website at <http://www.bmreports.com/bsp/DetailedSystemPricesHistoric.htm>
3. We choose for consistency only the ‘buy’ stack, i.e., the price at which additional capacity would be generated if the system was ‘short’ of electricity.
4. For each matched bid, we extract the generation unit and its contracted volume bid price. We also look up the generation type of each generation unit using the cross-reference available at www.bmreports.com/bsp/staticdata/BMUFuelType.xls
5. Since there are often several trades for a given generation type in a single period, with widely differing volumes of electricity in each trade, we take the volume-weighted average price of the trades executed in the given period, grouping them by generation type.

As the full bid stack has only been published since 5 November 2009, we restrict this part of the analysis to the period 5 November 2009 to 29 February 2012.

We now have the price of each accepted bid in the balancing mechanism by generation type. However, we note that electricity bid prices within a generation type varied over the period due to variations in reserve capacity, *and* due to variations in the underlying fuel price. In order to remove the effect of the underlying fuel prices, we also obtain prices for the underlying fuel for each generation type, specifically:

- For gas (CCGT and OCGT), we use UK natural gas futures traded on the ICE. These are specified for delivery at the ‘national balancing point’ in the UK, thus this benchmark closely matches gas prices likely to be paid by electricity generation using gas.
- For oil, we use the Brent crude oil futures price.

³ We asked Elexon whether submitting higher offer prices at times of low reserve capacity was legal under the UK Balancing Code. An analyst replied that generation units can submit whatever price they wish, but he believed that the market is sufficiently competitive that such a strategy would be unlikely to succeed in securing higher prices (Xing, 2012).

- For coal, we use the 'API2' benchmark, described by the publisher, Argus McLoskey as 'the reference price benchmark for coal imported into North Western Europe'.
- For the other generation types seen in the balancing mechanism (pumped storage, conventional hydro), we make no correction. Nuclear and wind generation types, although present in the UK (5% of electricity is wind power at the present time), have never appeared in the trades on the Balancing Mechanism, due to their lack of schedulability and sole use as base-load generators.

When necessary (for coal and oil), we convert these fuels costs from US\$ to UK £ using the prevailing \$/£ exchange rate. In all cases, we use the nearest-to-expiry Future price as a proxy for the spot price, with the assumption that most fuel for electricity generation is bought on the spot market and not hedged.

We will examine below how to adjust the various electricity trade prices for the underlying fuel costs, before comparing with reserve capacity.

Having calculated the traded electricity price for changes in the underlying fuel cost, we then compare reserve capacity against electricity price within a given generation type.

Results

Background – The History of Capacity and Demand

Firstly, it is helpful to observe the evolution of demand and capacity over the study period. We plot these in Figure 2. Note the seasonal pattern of demand, with winter peaks and summer troughs. The 'roughness' in each series is caused by the weekly seasonality, with demand typically much lower during each weekend than the 5 weekdays. In the centre of each winter, a sudden spike of lower demand can be seen, corresponding to the Christmas holiday period. In addition, there are occasional spikes upwards during each winter peak, corresponding to short periods of extremely cold weather. Capacity is also seasonal, since power stations using more expensive fuels are typically mothballed during the summer months when it is clear that their output is not needed. This effectively creates an economic upper bound to reserve capacity.

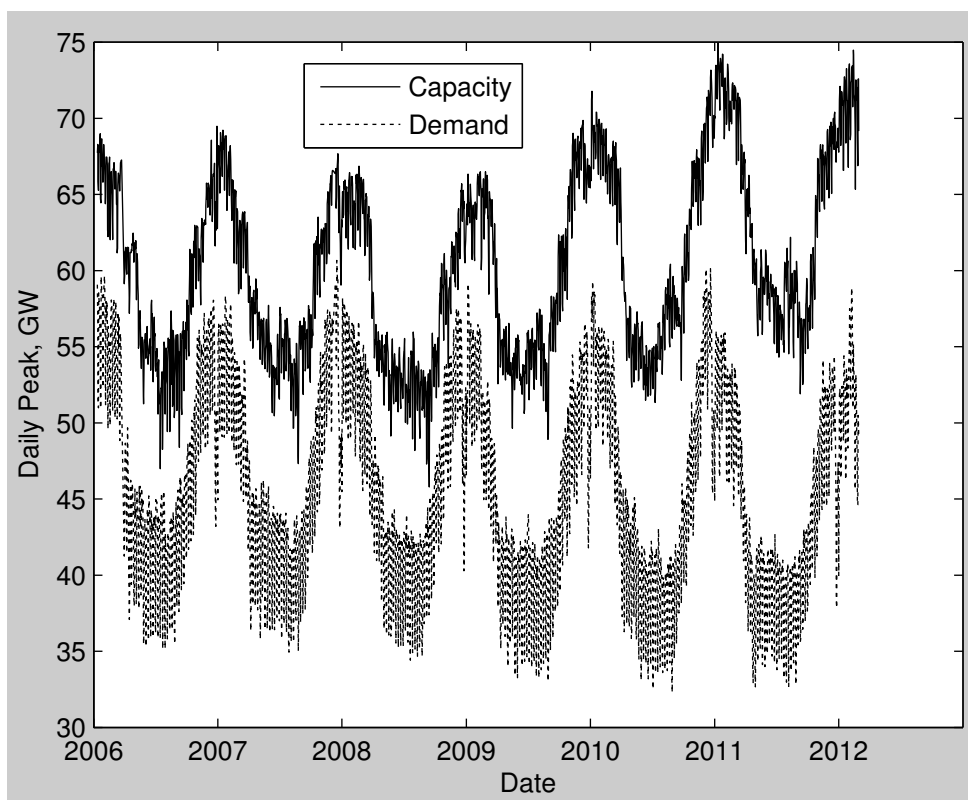


Figure 2 – UK Electricity Capacity and Demand, 2006-2012

In Figure 3 we plot the difference between capacity and demand, i.e., reserve capacity. We observe 3 periods, during the winters of 2007, 2008 and 2009 when reserve capacity fell to 0 or below. Since we used 2 day-ahead capacity forecasts, presumably additional emergency capacity was brought online during these times in response to the critically low forecast value. Reserve capacity has risen markedly since 2011, as several new gas-fired and wind power stations have come online. Arango and Larsen (2011) argue that electricity markets exhibit cycles of over- and under-capacity, triggering under- and over-investment respectively, and find statistical evidence in several electricity markets, including the UK's. We can note that this feature holds for most commodity markets. The wide range of reserve capacity over the study period, from 0 to over 20GW (which represented 50% of demand during Christmas 2011), gives us excellent data to study the varying effects of reserve capacity on electricity prices.

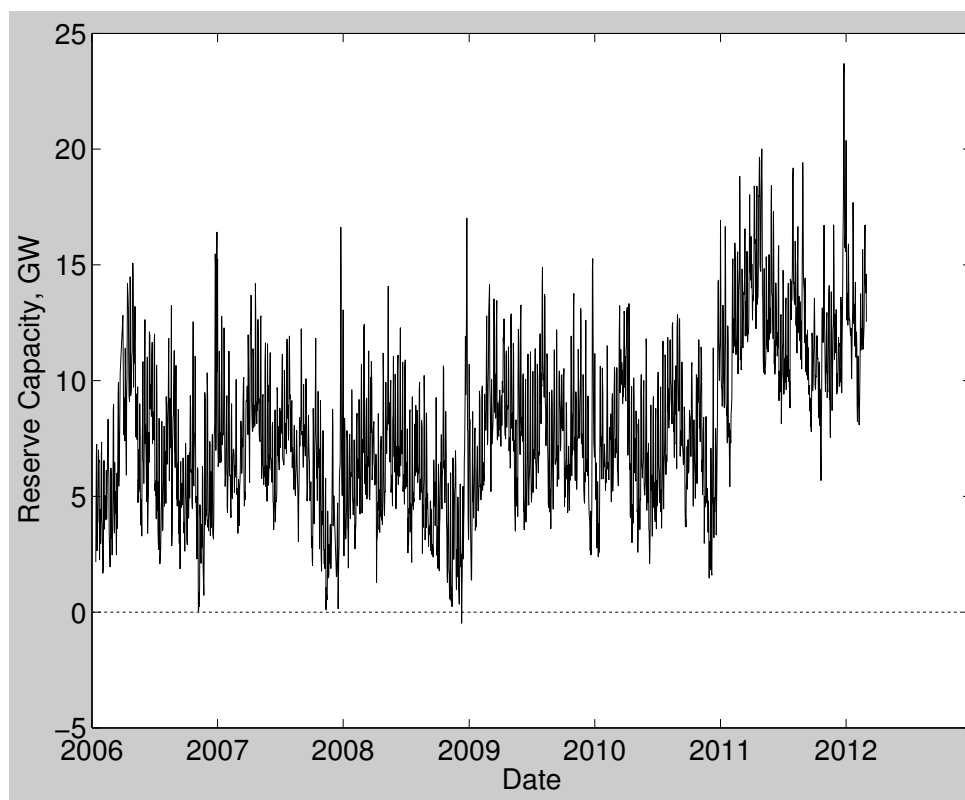


Figure 3 –UK Electricity Reserve Capacity, 2006-2012

The Relationship between Price and Reserve Capacity

We move now to our central result. Recall that the theory of storage shows rising volatility and price during low inventory, with a strong non-linear response as inventory approaches zero. Figure 4 shows the relationship between price (daily peak) and reserve capacity (daily lowest value), with one point per day.

We observe a very strong relationship. Above about 8 GW of reserve capacity, prices remain subdued at around £50/MWh, with no days above £100/MWh. Below this, and particularly below 5 GW, prices are much more likely to be elevated (although this is not necessarily the case). As reserve capacity falls below around 2 GW, prices in excess of £100/MWh become the norm. The slight 'hump' in average prices above 10GW of reserve capacity is due to the recent rise in reserve capacity since 2011 (see Figure 3) and higher electricity prices since then, caused by higher prices in the generation fuels – In particular, the UK has two oil-fired power stations, each producing 100 MW or more and serving 1.8 million homes.

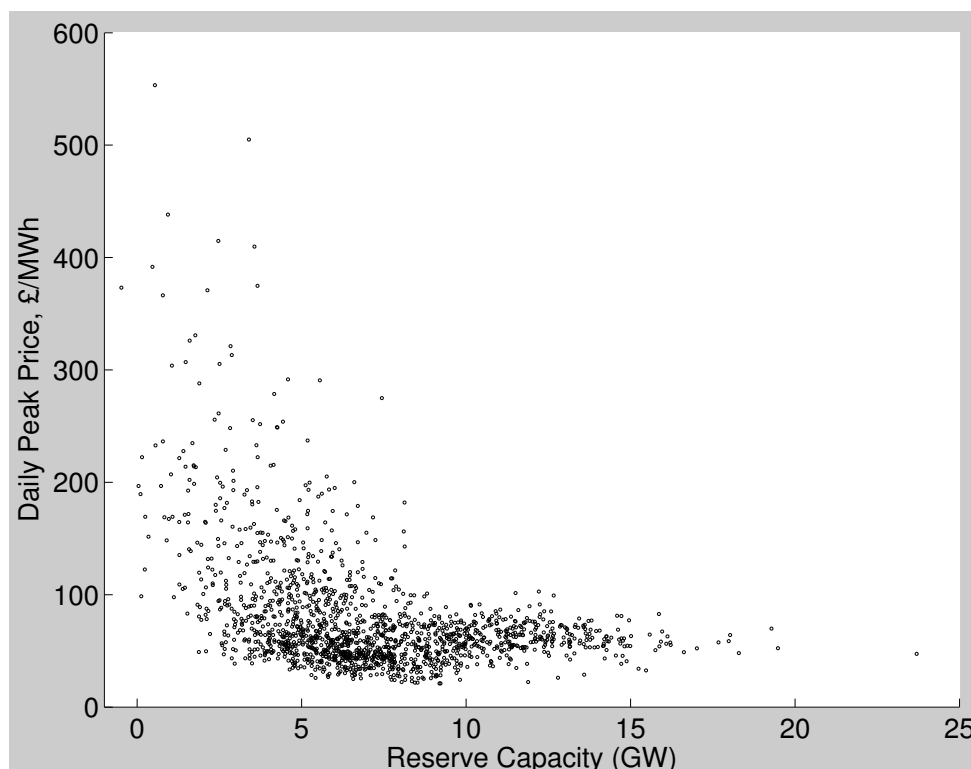


Figure 4 – Relationship between Daily Peak Electricity Price and Reserve Capacity

The Relationship Between Volatility and Reserve Capacity

Figure 5 shows the relationship between the daily price volatility and reserve capacity. We see a similar relationship for volatility as for price, with elevated values again occurring at low reserve capacity. The extremely high annualized volatility values⁴ demonstrate once more the unique features of electricity compared to other commodities – we observe that it is not uncommon for prices to *halve* from one half-hour to the next, an event never observed in equity indexes, and exceptionally rare in the case of individual stocks.

Note that both graphs replicate exactly the empirical results from the theory of storage, with the only change being the substitution here of reserve capacity for inventory.

⁴ Compared with annualized volatilities of around 10-20% for equities and 20-40% for most commodities, these annualized volatilities of 1000% are truly “off-the-scale”!

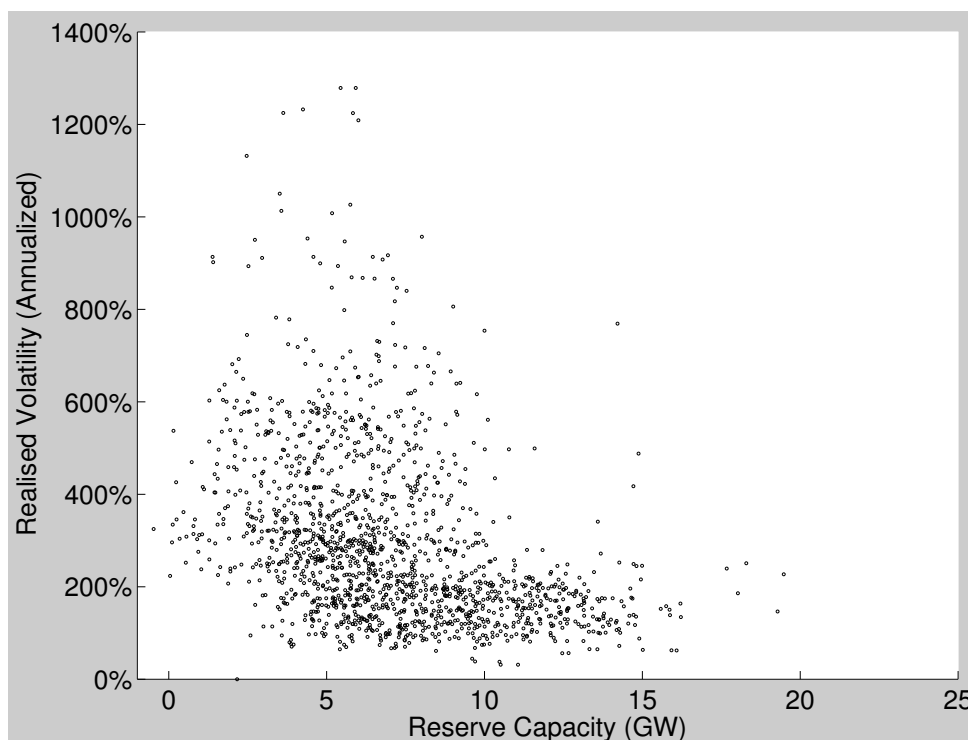


Figure 5 - Relationship between Daily Price Volatility and Reserve Capacity

Identifying the Source of the Price/ Reserve Capacity Relationship

In order to further investigate the relationship between reserve capacity and prices as displayed in Figure 4, we now look separately at the different types of fuel used in the ‘plant at the margin’.

We use our database of the UK electricity balancing mechanism trades from 5 November 2009 to 29 February 2012, to separate out trades by generation technology. The technologies observed, and the abbreviations used in the balancing mechanism data (which we follow) are:

- OCGT and CCGT – the two gas-fired turbine technologies
- COAL – coal fired
- OIL – oil fired power stations
- PS – hydropower, pumped storage
- NPSHYD – non-pumped storage hydropower (i.e., ‘conventional’ hydro-electric power).

We present in Figure 6 (a) and (b) the relationship between the trade price and the overall system reserve capacity for the case of PS and NPSHYD, with no correction for the input fuel. The graphs are therefore directly comparable with Figure 4.

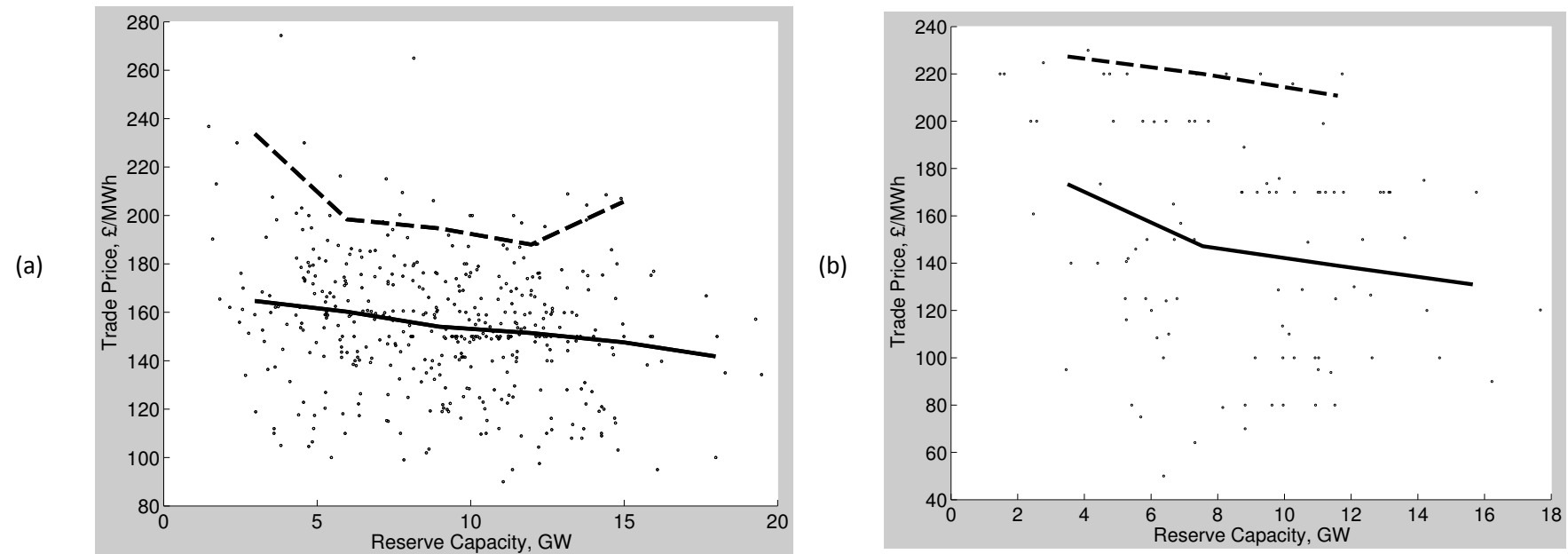


Figure 6 - Relationship between Daily Peak Electricity Trade Price and Reserve capacity for (a) Pumped Storage and (b) Conventional Hydro-electric generators. The solid line represents the median and the dotted line the 95th percentile.

In each case, we fit two trend-lines, by ‘binning’ points into a small number of bins of reserve capacity. The solid line is based on the mean trade price in each bin. The dotted line is based on the 95% percentile in each bin. We only construct the line in those bins with sufficient data points.

We note that firstly, the trade prices are quite high compared to the ‘system’ price of Figure 4. The calculation of the ‘system’ price from individual trades in the balancing mechanism is based on a relatively complex methodology (Elexon 2009b). Prior to 2006, a volume-weighted average price of balancing mechanism trades was used. However, generators successfully lobbied in 2006 for a change to this calculation. They argued that since the balancing mechanism facilitated the short-term ‘top up’ of electricity production over and above the medium-term contracts already executed, the system price should reflect the marginal price of the electricity generation, not the average price. The calculation was duly changed so that only the highest-priced 500MWh of trades would be averaged to calculate the system price. This justifies our inclusion of the dotted line at the 95th percentile.

Secondly, we note that as expected, pumped storage hydroelectricity is more expensive in general than the regular hydroelectricity.

Lastly, we observe in both cases a moderate but visible downward slope in prices as reserve capacity increases.

In the case of the fuel-fired generation types (‘OIL’, ‘COAL’, ‘OCGT’ and ‘CCGT’), we initially plotted trade price against reserve capacity and found no slope in the fitted curves (for example, see Figure 7, for CCGT). This analysis, however, ignores the strong relationship between electricity prices and the *underlying* fuels costs. Demonstrating this relationship, we plot in Figure 8 a smoothed⁵ system electricity price and the contemporaneous UK gas spot price, and a strong dependence is visible.

⁵ We produce a daily series of ‘smoothed’ electricity prices by taking the average daily system price, and then averaging the daily values over a 30-day window.

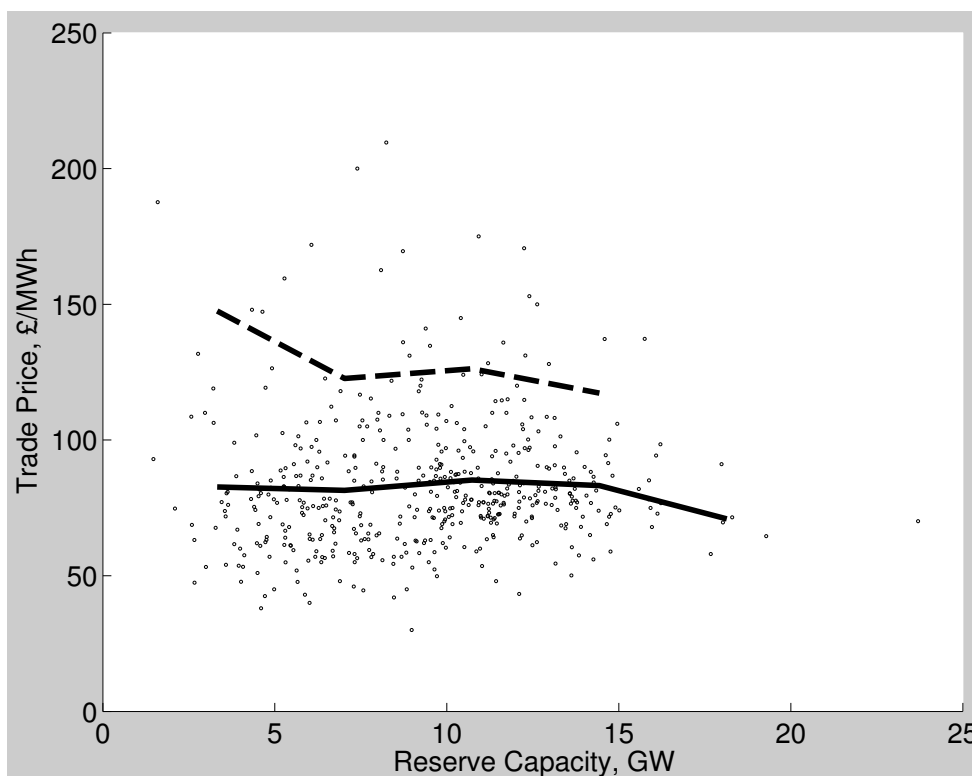


Figure 7 - Relationship between Daily Peak Electricity Trade Price and Reserve capacity, CCGT Gas (No adjustment for input fuel cost).

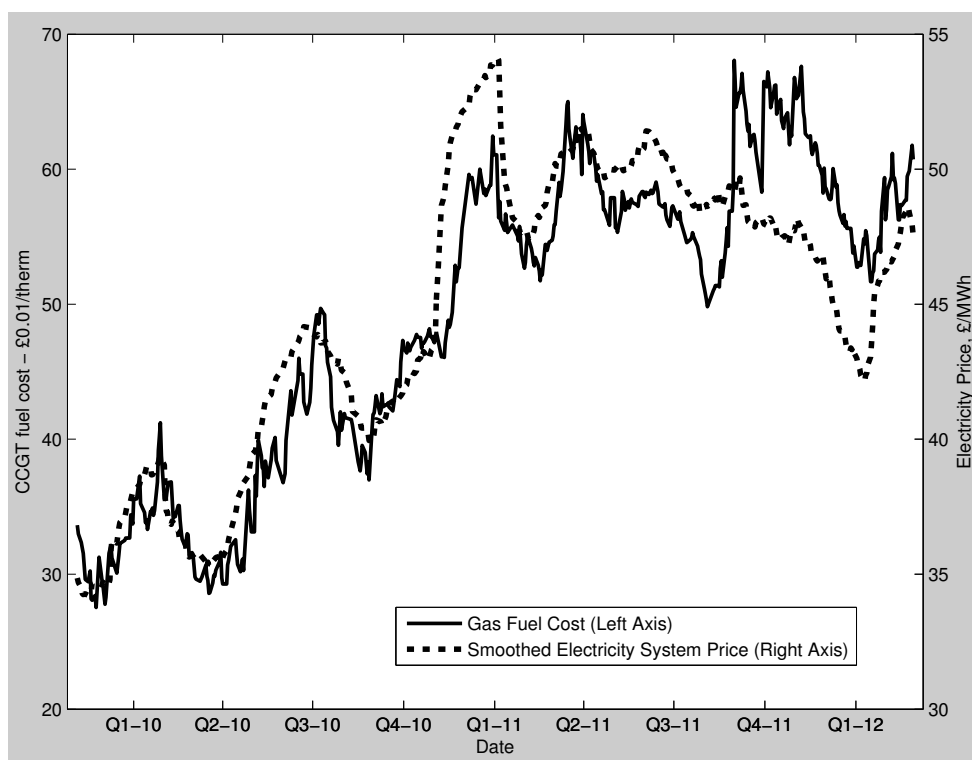


Figure 8 – UK Gas Price and Smoothed Electricity System Price, Nov 2009 – Feb 2012

To separate the effects of reserve capacity and fuel prices on electricity trading prices, we conducted regressions for the price of electricity produced by each generation type against their specific input fuels costs. We write as an example Equation 2, for the case of CCGT power stations producing electricity with daily peak price $S_{\max,j}^{\text{electricity_CCGT}}$, using gas with price S_j^{gas} as the input fuel and the lowest reserve capacity on that day of $RC_{\min,j}^{\text{outturn}}$ (measured in MW).

$$S_{\max,j}^{\text{electricity_CCGT}} = b_0 + b_1 S_j^{\text{gas}} + b_2 \frac{1}{RC_{\min,j}^{\text{outturn}}} \quad (2)$$

To reflect the non-linearity of the relationship between price and reserve capacity observed in Figure 4, we regress electricity price against the quantity $\frac{1}{\text{reserve capacity}}$, following Geman and Nguyen (2005), who found that introducing ‘scarcity’, defined as the inverse of inventory, gives a good linear fit with price volatility. Defining N as the number of data points available for each regression, with one point per day in which the given generation type appeared at the peak period, we display the regression results in Table 1.

Generation Type	CCGT	OCGT	COAL	OIL
Underlying Fuel	Gas		Coal	Oil
N	500	100	425	20
Lowest input fuel price: $\min_j(S_j^{\text{underlying}})$	UK pence 27.54 / therm		£45.75/t	£44.14/bbl
Highest input fuel price: $\max_j(S_j^{\text{underlying}})$	UK pence 68.06 / therm		£85.21/t	£69.80/bbl
b_0	27.36	327.29	44.45	-37.76
b_1	0.9077	-1.9736	0.5628	3.627
b_2	83592	120054	9239	568836
R^2	0.15	0.265	0.06	0.433

Table 1 – Summary Statistics and Regression Results between Electricity Price, Reserve capacity and Underlying Fuel Price for various Generation Types

The strongest relationship holds for oil with an R^2 of 0.433; however the value of $b_0 < 0$ casts doubt on this regression, perhaps caused by the low sample size, $N=20$. The signs of all other fitted parameters are as expected, except the value of b_1 for OCGT. We did not necessarily expect high values for R^2 - we can see from Figure 6 that the relationship between reserve capacity and price is 'noisy'.

Using the coefficient of b_1 from the above regression, we can then derive an 'input fuel - adjusted electricity price' for natural gas, and similarly for the other fuels:

$$S_{\max,j}^{electricity_CCGT_adjusted} = S_{\max,j}^{electricity_CCGT} - b_1 S_j^{gas} \quad (3)$$

If we now plot these adjusted electricity prices against the system reserve capacity, we obtain Figures 9(a) – CCGT, 9(b) – OCGT, 9(c) – COAL and 9(d) – OIL.

In all cases except coal, we observe a marked (but not large) increase in price for lower values of reserve capacity. The unexpected results for coal, with a slight *increase* in price as capacity increases based on the trend lines, may be caused by a lack of trades for either particularly high or particularly low values of reserve capacity. In the case of oil, we have insufficient data to plot a 95th percentile trend-line.

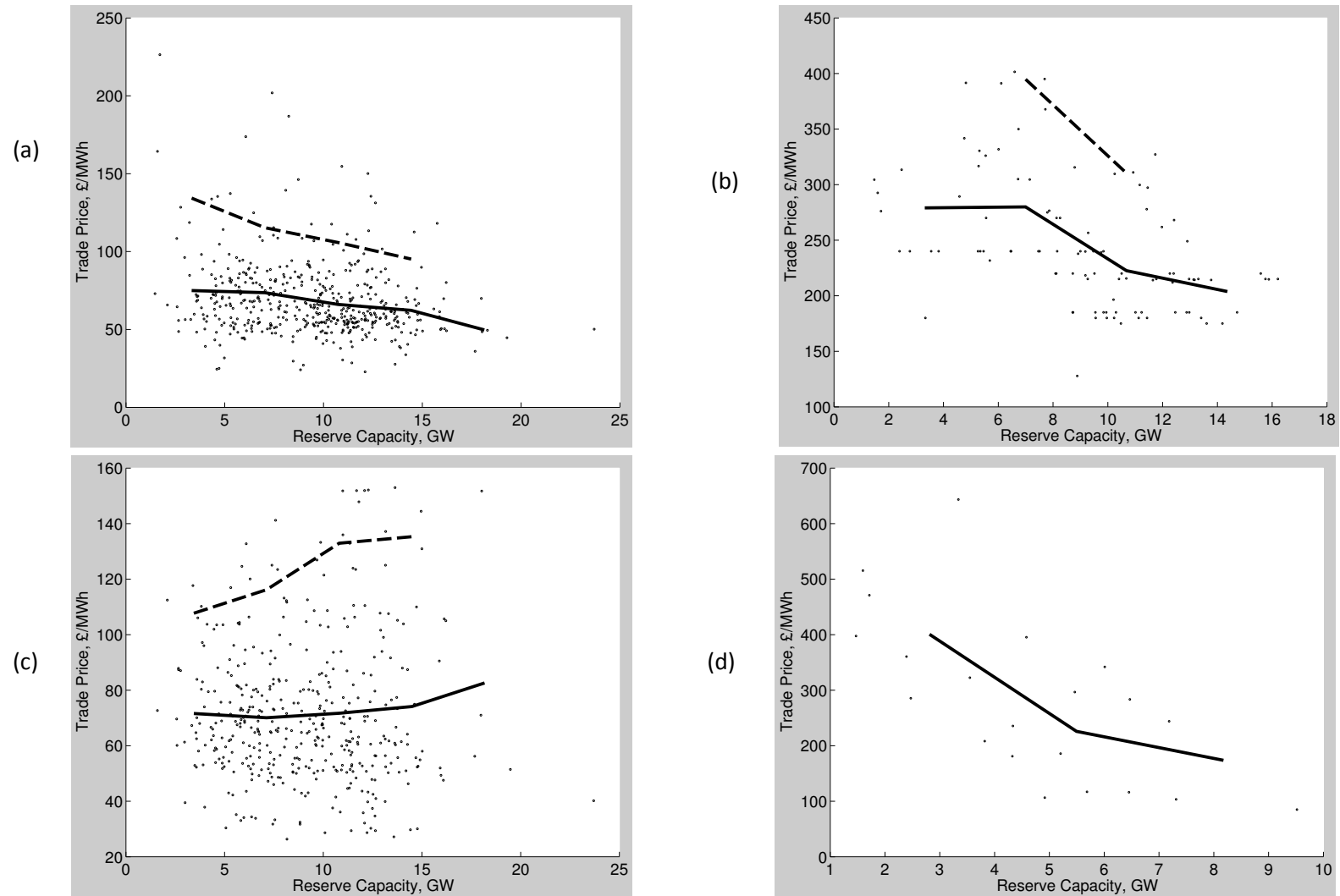


Figure 9 - Relationship between Daily Peak Electricity Trade Price (Adjusted for Fuel Price) and Reserve Capacity for (a) CCGT (b) OCGT (c) COAL and (d) OIL.

Finally, we take our individual trend-lines and combine them in Figure 10. This shows the individual contribution of each generation type to the overall price-capacity curve. With the exception of coal, most of the curves are upward sloping to the left, but only weakly. The lowest mean prices are those of gas (CCGT) and coal, typically lower than £100/MWh. Next in the pricing hierarchy comes both conventional hydro and pumped storage, with mean prices around £150 per MWh, rising slightly at times of low reserve capacity. Only oil-fired power exhibits a steep curve, and only runs at times of low reserve capacity (<10GW), rising to £400/MWh. Highest overall in terms of average price are the inefficient OCGT gas turbines, which exhibit an increase in price during times of low reserve capacity.

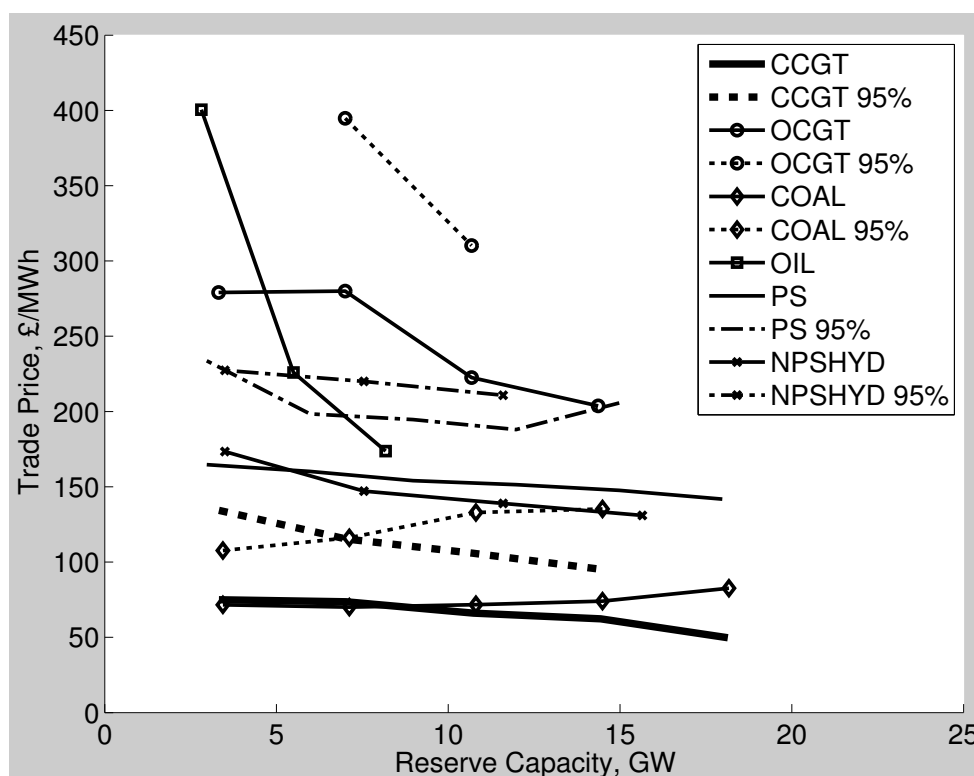


Figure 10 – Combined Price vs. Reserve Capacity Curve, broken down by generation type

Reserve Capacity Forecasting

Since reserve capacity provides valuable information about electricity prices (especially overall prices, as in Figure 5), we briefly examine how accurately reserve capacity can be forecasted. Assuming that the national grid forecasts are unbiased, we examine the relationship between the *out-turn* reserve capacity figure, the 2-day-ahead reserve capacity estimate, and the 14-day ahead estimate. Table 2 below shows some summary statistics. With a mean (out-turn) reserve capacity of 7920MW, the forecasters are able to predict the out-turn value within 2436MW (mean error) or 1913MW (standard deviation) a whole 2 weeks ahead. Information feeding into this forecast is likely to include seasonal norms of supply and demand as well as details of generators off-line for maintenance. By two days ahead, a reasonable prediction of weather should be available (and hence a better prediction of demand) as well as more accurate capacity data; generators, however, are only obliged to supply details of which plants they will run by 11am on the day preceding the generation day. Two days in advance, the prediction error has fallen to 764MW (mean) or 788MW (standard deviation), being in both cases less than 10% of the mean reserve capacity value.

Series	Mean	Standard Deviation
Out-turn reserve capacity (MW)	7920	3479
Absolute error between 2 day forecast and outturn (MW)	764	788
Absolute error between 14 day forecast and outturn (MW)	2436	1913

Table 2 – Accuracy of Reserve Capacity Forecasts, January 2006 - Feb 2012

Spare Capacity and Crude Oil Prices

We now turn to the crude oil market, and investigate whether spare capacity (the usual term for reserve capacity in crude oil markets) is also useful as an explanatory factor for prices.

The first major effort in developing models to explain the price of oil goes back to the 1970s in response to the price shocks encountered at that time. Different explanatory factors were proposed, among them the spare capacity in the oil production industry defined as the extra extraction capacity that could rapidly be brought online if necessary, above current capacity. Over the period 1990-2005, the rising popularity of ‘reduced- form’ oil models has seen spare capacity lose its popularity as an explanatory factor. An isolated mention is in Kaufmann et al. (2004) who find that it helps to explain oil prices, but their study period ends in 2000.

The growth of stochastic modelling of commodity spot prices to price derivatives began with the important paper by Gibson and Schwartz (1990). A large family of factor models followed, some of them incorporating mean- reversion in prices to reflect the range-bound values prevailing in the 1990’s and early 2000’s. Most of these models included a small number of state variables, hence their classification as ‘reduced- form’. From 2003 onwards, the rapid rise of oil and other commodity prices has led a number of authors to reconsider mean-reversion in commodity prices, see for instance Geman (2005). Our view is that recent unprecedented rises and falls in commodity prices lend support for a return to structural models, as proposed by Pirrong (2011), incorporating economic fundamentals, like in the world of credit instruments.

Data and Model Description

We now propose a model that uses two fundamental factors – spare capacity and inventory – to predict crude oil prices. The data are sourced as follows.

Oil Prices

For global oil prices we chose Brent oil futures prices, which are principally traded on the ICE⁶. Brent prices are to be preferred as a world benchmark over WTI, the other major

⁶ The Intercontinental Exchange, based in Atlanta, which purchased the IPE (International Petroleum Exchange) in 2001, shifting Brent oil trading from London floor-based trading onto its all-electronic platform in 2005.

benchmark, since US-focused WTI prices have become dislocated from the world market in the post-2008 period due to technical reasons⁷. In the period prior to 2008, Brent and WTI moved in tandem, thus either Brent or WTI could be considered a good measure of world oil prices up to that date. We take monthly average prices of the front-month oil contract, itself a proxy for spot prices.

Spare capacity

Spare capacity in crude oil extraction is typically concentrated in OPEC countries, since OPEC's quota system places formal restrictions on the oil extraction rate of its oil member countries. Although in theory non-OPEC countries may also produce less than their full capacity, only data for OPEC spare capacity is available. OPEC itself does not publish its own spare capacity values, but estimates are available from the EIA (the Energy Information Administration of the US), via the data browser within its 'Short Term Energy Outlook (STEO)' reports (EIA 2012). Monthly data are available from January 1993 onwards, which limits our study period to be January 1993 to June 2012. We convert OPEC spare capacity (quoted in million barrels per day) into a percentage by dividing by total daily world oil consumption, again from the STEO database.

Inventory

To measure inventory, another fundamental variable, we would hope to combine inventory data for all commercial inventories worldwide⁸. However, the closest approximation to this which is released on a monthly basis is the total inventory for all OECD countries, again reported by the EIA. For many years, oil consumption in OECD countries dwarfed that of the non-OECD countries, and OECD data were a good proxy for the world total (Figure 11). However, the OECD countries, with their comparatively low economic growth rates, have been able to reduce their total oil consumption since the price rises experienced as of 2002, whereas the non-OECD countries (in particular China and Saudi Arabia) have witnessed huge growth in their oil consumption. Unfortunately, non-OECD inventory data are unavailable. China reports inventory data, but usually as a change rather than an absolute value; and it is

⁷ Factors causing the WTI benchmark to become dislocated from world oil prices include the huge inventory build in Cushing, Oklahoma, (the pricing point for WTI) and the relative difficulty in moving oil away from Cushing once it arrives there; also the growth in domestic US oil production due to the growth in the 'fracking' advanced recovery technique, and the fall in domestic consumption.

⁸ Commercial inventories influence the market more than Government emergency (strategic) inventories (Saif Ghouri 2006). Strategic oil inventories such as the US Strategic Petroleum Reserve are typically only intended to be released in times of crisis, rather than to moderate prices (US Department of Energy 2012).

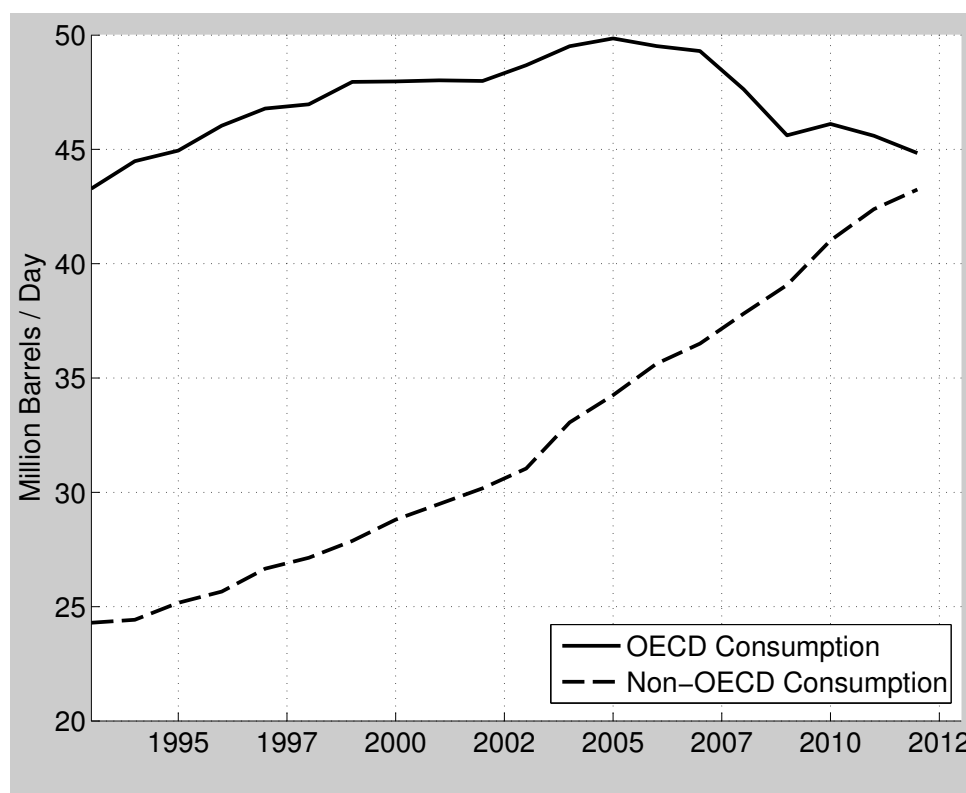


Figure 11 – Daily Oil Consumption of OECD and non-OECD Countries (annual average)

thought to be building and filling large strategic oil reserves, at a rate that is not published regularly. Saudi Arabia's national oil company (Saudi Aramco) is known to have large storage capacity located worldwide, but the quantity of oil actually held is not regularly published either (Bloomberg 2012). We therefore use the OECD commercial inventory (again from the STEO database) and convert this to a percentage of annual total world oil consumption. Figure 12 shows the evolution of these measures of spare capacity and inventory over the study period of January 1993 to June 2012. Notable is the relatively constant value of OECD inventories, despite the growth of non-OECD consumption. Also particularly prominent is the sudden drop to extremely low values for OPEC spare capacity – around 1% of consumption – in the period 2003-2008, co-incident with the large price rises experienced over that period. Spare capacity has since returned to around 3-4%, but is once again falling.

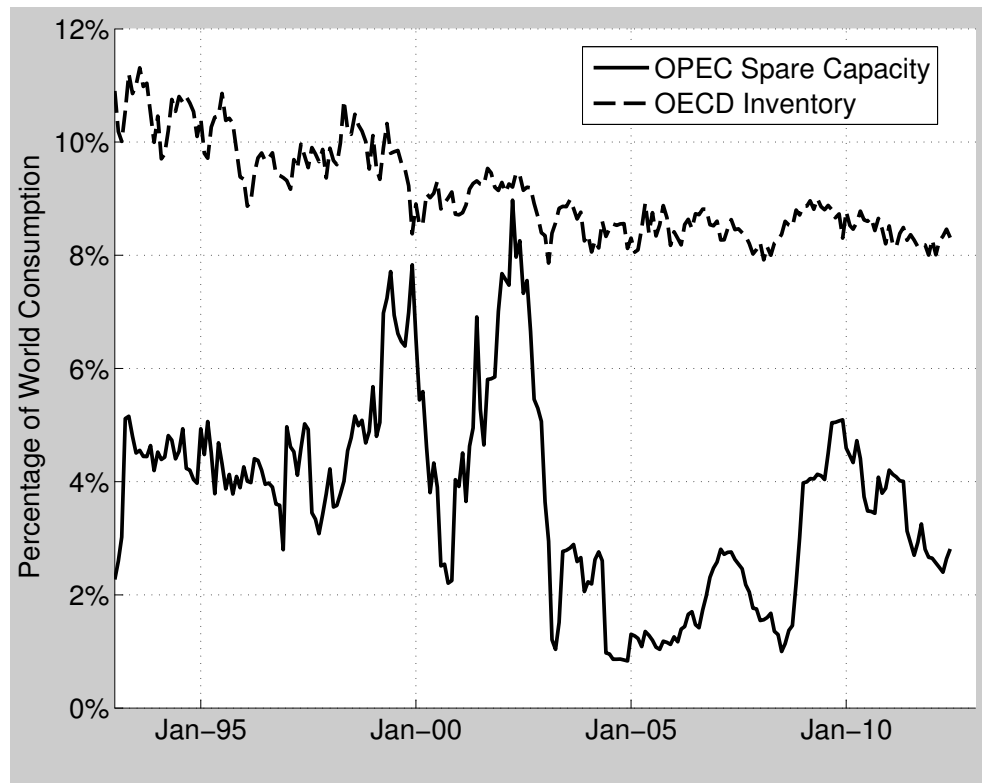


Figure 12 – The evolution of crude oil spare capacity and inventory over the study period

Variable Transformation

We define spare capacity SC_t as a percentage of world consumption and inventories INV_t as a percentage of *annual* world consumption. In order to illuminate situations where our key variables deviate from their average values, possibly creating tensions in the markets (see Geman and Ohana (2009)), we define two new series by subtracting from the original ones their means over the full study period T ,

Namely

$$\overline{SC}_t = SC_t - \underset{t \in T}{mean}(SC_t) \quad (4)$$

$$\overline{INV}_t = INV_t - \underset{t \in T}{mean}(INV_t) \quad (5)$$

A Fundamental Model for Crude Oil Prices

Our price variable is the front-month Brent oil futures prices denoted S_t , and the model variables spare capacity \overline{SC}_t and OECD inventory \overline{INV}_t . We now propose our price prediction model in the form:

$$P_{t,\theta} = P_0 e^{(-k \cdot \overline{SC}_t - l \cdot \overline{INV}_t + m \cdot t)} \quad (6)$$

where $\theta = \{P_0, k, l, m\}$ is a vector of model parameters, all positive; t is the number of years since the start of the study period, 1st January 1993, and $P_{t,\theta}$ is the price at time t given θ .

This formulation expresses the price as a positive exponential of time starting with the value P_0 at $t = 0$ and growing at an annual rate m , with this growth monitored by the two fundamental factors. The negative multiplier for parameters k and l indicate that we expect an increase in spare capacity – *ceteris paribus* – to reduce the rate of price growth, and similarly so for inventory.

We calibrate the parameter vector θ by minimizing the total mean square error between the model price $P_{t,\theta}$ and the market price S_t over the study period T , i.e., we choose the parameters $\hat{\theta}$ such that

$$\hat{\theta} = \arg \min_{\theta} \left(\sqrt{\frac{1}{T} \sum_{t=1}^T (P_{t,\theta} - S_t)^2} \right) \quad (7)$$

In order to investigate the performance of the two fundamental factors, we tested the following nested models:

1. ‘No fundamentals’ – we model the price with just constant growth rate m , constraining parameters k and l to 0.
2. ‘inventory only’ – we constrain parameter k to 0
3. ‘spare capacity only’ – we constrain parameter l to 0
4. ‘both’ – we perform the unconstrained calibration, i.e., with both fundamental factors included.

Results for the Crude Oil Model

The results of the four calibrations are shown in Figure 13, with the parameters and the mean pricing error displayed in Table 3. We also report in Table 3 an alternative measure of model accuracy, the mean absolute error ('MAE') in pricing, defined as:

$$MAE = \frac{1}{T} \sum_{t=1}^T |P_{(t,\theta)} - S_t| \quad (8)$$

Model	P_0	k (spare capacity)	l (inventory)	m (drift)	RMS Pricing Error	MAE Pricing Error
No Fundamentals	10.32	-	-	12.5%	\$12.70	\$8.64
Inventory only	11.56	-	33.66	10.5%	\$11.48	\$8.15
Spare capacity only	9.52	10.18	-	12.6%	\$10.63	\$7.58
Both	10.09	8.35	13.23	11.8%	\$10.50	\$7.59

Table 3 – Crude Oil Price Model Calibration Results

The results (Table 3 and Figure 13(a)) indicate that even the 'bare' model, with simple exponential growth, reasonably describes the trajectory of crude oil price from 1993 to mid-2012. The model under-estimates prices in the earlier years (before 1997), lending support to those who argue that crude oil underwent a 'regime shift' shortly after 2000, with prices being mean-reverting before that time. Notable is the high annual growth in oil prices represented by the value of 12.5% for the m parameter.

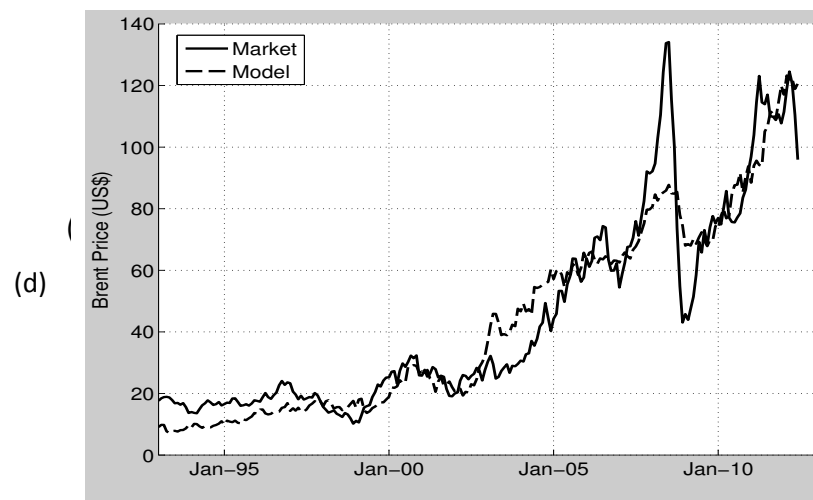
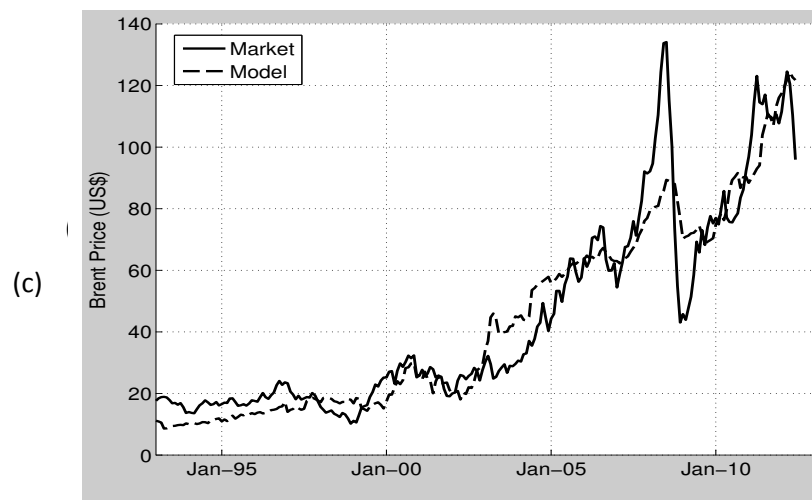
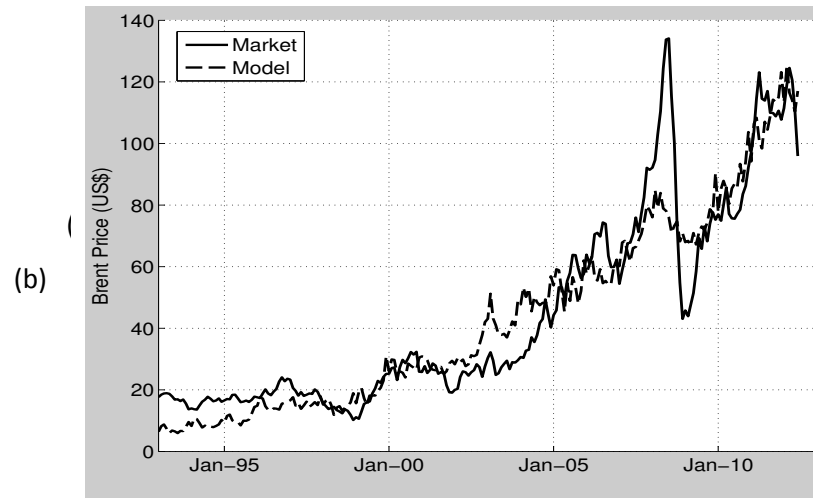
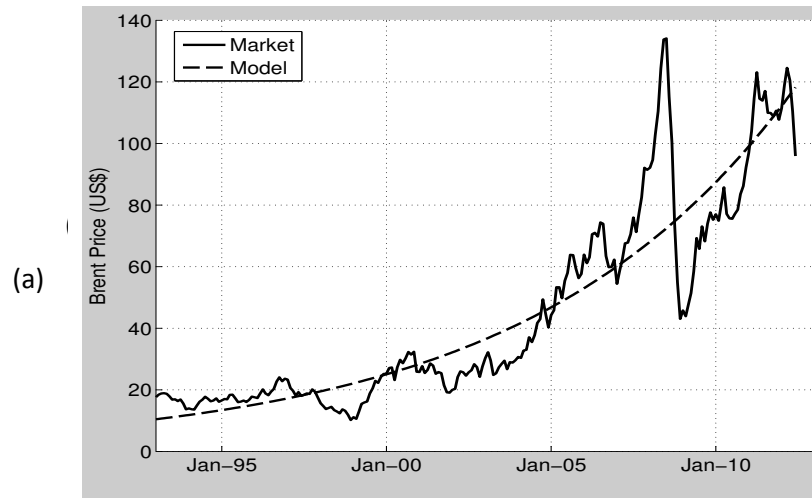


Figure 13 – Crude Oil Price Model Calibration Results, showing Market and Model Price for (a) No Fundamentals (b) Inventory Fundamentals only (c) Spare Capacity Fundamentals Only (d) both Inventory and Spare Capacity Fundamentals

Adding inventory data improves the model slightly – we see the two measures of error falling slightly. Figure 13(b) shows that the variations in inventory produce a sharp rise in ‘model’ oil prices around 2003. The market price had begun to rise earlier, in 2002, but the initial rise was less sharp. The market price continued rising, leading eventually to a short-lived speculative bubble with Brent oil prices peaking at \$146 in mid-2008 (we display monthly averages, hence the charted price is slightly below the highest daily close of \$146.08 attained in early July 2008). The model price predicts a more modest rise (i.e., based only on fundamentals), up to around \$80. The subsequent collapse in market prices to around \$40 in January 2009, shortly after the demise of Lehman Brothers, is also considered by the model as an over-correction, reinforced by the market price’s rapid return to \$80 (the model value) by January 2010.

Moving to the models incorporating spare capacity, Figure 13(c) and 13(d) visually appear little different from the inventory-only model of 13(a), although the ‘fundamentals’ price in the 2008 boom rises to \$90 instead of \$80. Examining the calibration accuracy (Table 3), however, shows that the addition of spare capacity greatly reduces the pricing error of the model. The spare-capacity-only model itself reduces the pricing error by roughly twice as much as the inventory-only model, for both the RMS and MAE measures. Furthermore, once spare capacity is included in the model, also including inventory gives little or no further reduction in pricing error.

We would not expect a model incorporating spare capacity to perfectly model oil prices in the short term. Consider a hypothetical example where the market is constrained with only 1.5 mb/d of spare capacity. Imagine an OPEC meeting then raises OPEC’s combined production quota by 1 mb/d with a reduction of spare capacity to 0.5 mb/d. Although this is a sign of scarcity, implying higher prices in the medium term, the more immediate effect of the OPEC decision to raise production will likely be a *lowering* of prices due the increased supply. Our model does not target these short-term dynamics.

We thus conclude that for the modelling of absolute oil prices, the spare capacity fundamental provides valuable explanatory power, more so than inventory numbers.

The EIA not only publishes all necessary data for our price prediction model (global consumption, OECD inventory, spare capacity) for the past months, it also forecasts all these values up to 2 years into the future. Using these forecasts allows one to predict the future trajectory of Brent oil prices. This trajectory is displayed in Figure 14. We continue to calibrate

the model using all data from January 1993 to June 2012, but plot the period January-2006 to December-2013. The model does not forecast the sudden recent drop in crude prices (related to the western economic crisis, and fears of worldwide contagion). With spare capacity forecast to grow from 2.3 mb/d (May 2012) to 3.5 mb/d (December 2013), the model currently⁹ predicts oil prices will continue to rise, but at a reduced rate compared to the recent past, reaching around \$135 by the end of 2013.

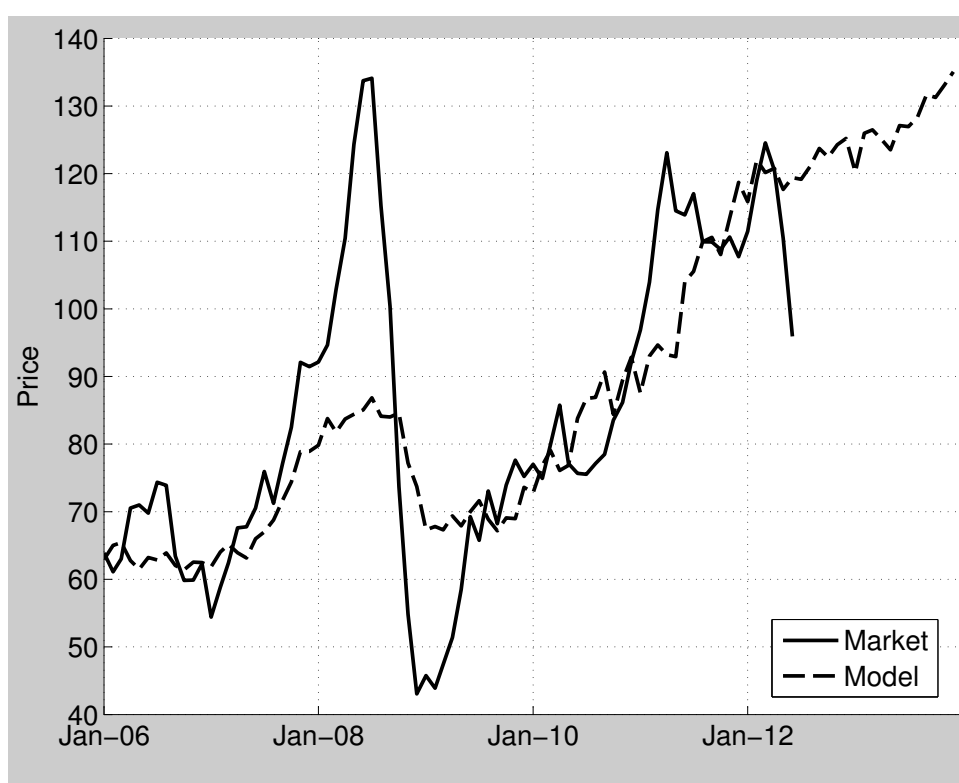


Figure 14 – Model Prediction of Crude Oil Price to December 2013.

Obviously, a severe political crisis in a crucial country like Saudi Arabia would translate into a dramatic move in the observed price trajectory – an issue not discussed in this paper.

⁹ Based on the EIA forecasts as at 1st July 2012.

Conclusion

Electricity is the archetypal ‘non-storable’ commodity, and the UK, with its low proportion of electricity generated from hydro sources, is a good example of a non- hydro market. In principle, Working’s theory of storage cannot apply to non-storable commodities, as indicated by its very name. We have argued that using the concept of ‘margin reserves’ in place of inventory, the theory of storage may be extended to electricity.

We have shown that two key relationships can be observed:

- Spot prices rise during periods of low reserve capacity, increasingly rapidly at times of extreme scarcity
- Spot price *volatility* also rises in a corresponding way

We have shown that the strength of the price-reserve capacity relationship is primarily related to the point of the ‘bid-stack’ that satisfies demand. We also noted that electricity reserve capacity can be forecast some days before the day of generation. Even two weeks ahead, a reasonable estimate can be made, and by two days ahead, system operators (ISOs) can estimate reserve capacity with a margin of error of less than 10%. Such predictions clearly provide information for predicting electricity price and volatility.

Based on the strong overall results linking reserve capacity with price and volatility, we propose that Working’s original theory of storage can be expanded to electricity, by the substitution of margin reserves to inventory. These results also reinforce the argument that any model for electricity spot prices should incorporate reserve capacity, as proposed by Cartea, Figueroa, and Geman (2009).

Turning to crude oil, we have proposed a definition for spare capacity and shown its relevance as a fundamental factor to explain oil prices. Indeed, the explanatory power of spare capacity is greater than that of inventory.

In summary, we have shown that reserve capacity is an important fundamental factor in energy markets; models for price or volatility are likely to be incomplete without its inclusion.

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Chapter 4

Novel Methods of Detecting Agricultural Scarcity

Abstract

Agricultural prices have risen sharply in recent years, with the World Bank food index rising 3-fold between 2000 and 2011. Most explanations focus on *scarcity*, with a mismatch between rapidly rising demand meeting constrained supply. Unlike metals and fossil fuels, agricultural commodities have no measure of ‘reserves’ to give us long-term supply information; financial markets instead focus heavily on inventory, specifically the ‘stocks-to-use ratio’, which has fallen in recent years. We examine the four most widely grown agricultural products (corn, wheat, rice and soybeans), and propose several other methods of detecting ‘scarcity’ which could warn of future supply constraints. In particular, we describe a method of estimating ‘spare capacity’, being additional acreage that could be planted in the next crop year, as well as using ‘yield-at-risk’ to put inventory into context by estimating a ‘yield-at-risk coverage duration’. Corn and soybeans repeatedly exhibit signs of scarcity, whereas wheat and rice show less cause for concern.

This chapter and its analysis were completed in May 2012, before the recent US drought began. Our warnings that soybeans and corn exhibit multiple signs of scarcity, and that world consumers are strongly exposed to the output of the US and Brazil, now seem remarkably prescient, with price rises between early June 2012 and mid-August of 60% (corn), 30% (soybeans) and 40% (wheat).

Introduction

Unlike the case of metals and fossil fuels, there are no ‘reserves’ for agricultural products. For a given crop, each year some is planted, grown and harvested, and some is consumed. That which is not consumed is stored in inventory, linking one year to the next. The ratio of this inventory to yearly consumption (the so-called ‘stocks-to-use’ ratio) is therefore a closely followed value in agricultural commodities since inventories serve as an important buffer, absorbing both short-term shocks in demand and, more importantly for agricultural products, protecting against (negative) shocks in supply, often caused by adverse weather.

The stocks-to-use ratio provides some information about short term scarcity or abundance. But, with stocks-to-use ratios of typically between 10% and 30% of annual consumption, inventory values provide only short-term information¹ since inventory of 10% could be exhausted in a single bad year – global corn production fell 11% in 1993 from the previous year, and dropped a disastrous 21% in 1983 mainly due to extreme drought in the US. To examine whether we will observe scarcity in the medium or long term, we need other methods.

Estimating Long Term Agricultural Demand

Studying agricultural scarcity in the long term requires long-term projections of supply and demand. The UN FAO’s “Looking Ahead in World Food and Agriculture : Perspectives to 2050” (FAO 2011), is the culmination of an extended series of expert consultations started a decade earlier (FAO 2002), updated in an ‘interim report’ (FAO 2006). It is perhaps the world’s best-informed study of the likely progression of agricultural demand and supply in the period to 2050. Its findings form the basis for our section below.

Focusing first on demand, there are three major factors. The food consumption of each person is strongly related to their wealth. Modelling population as P , income as I , food prices as S and consumption for a given level of income and food price as $C(I, S)$, total consumption is therefore $P \cdot C(I, S)$. We examine these in turn.

Population projections, at least in the medium term, can be considered as relatively precise. For example, world population projections for the year 2000 made in the early 1970’s

¹ By short term, we mean providing information only about the next 1-3 years. By long term, we mean 10-40 years hence.

by the UN Population Division were only 2.3% higher than the actual value observed 30 years after the prediction (Sohn 2007). The world population is expected to increase from 6.9 billion in 2010 to 9.3 billion in 2050 (UN 2010, central variant), an annual growth rate of 0.75%.

Income is somewhat harder to estimate, but most projections suggest moderate growth will continue, apart from a few outlying predictions of ‘world collapse’ (Meadows 1972; Meadows, Randers, and Meadows 2004). Sohn (2007) examines GDP projections made by the UN in 1973 using a so-called ‘World Model’ (Leontief et al. 1977), for which Leontief won the Nobel Memorial Prize. The projections for 2000 were only slightly higher than the outturn values (projection: 3.9% p.a. growth, outturn: 3.3%). World Bank projections of future GDP growth point to growth rates gradually falling from 5% p.a. to 4% p.a. (developing countries) and from 2% p.a. to 1% p.a. (developed countries), reported in FAO (2011). Rather than treat the world as a homogenous consumer, more accurate forecasts of food consumption can be obtained by modelling different countries and different income groups within countries separately.

Commodity prices are notoriously hard to predict even a few years into the future, let alone into the long-term. For example, Table 1 lists the price of soybeans predicted by futures markets for the November contract (shortly after harvest), displayed bi-annually for the period 2001-2011. We compare the price at which they were first traded (average traded price over the first 20 business days of trading) with the final traded price before expiry. It is clear that futures markets participants, who have an obvious financial interest in making accurate predictions, have great difficulty in predicting agricultural prices a mere 2-3 years into the future.

Date Prediction Made (Futures Contract Inception)	Date for Prediction (Futures Expiry Date)	Years Ahead	Prediction Price (Market Price at Contract Inception)	Market Price at Expiry	Variation between realised market price and prediction
October 1999	November 2001	2	531	448	-16%
March 2001	November 2003	2½	499	773	+55%
January 2004	November 2005	2	613	590	-4%
April 2005	November 2007	2½	599	1066	+78%
November 2006	November 2009	3	685	984	+44%
April 2008	November 2011	3½	1370	1172	-14%

Table 1 – Wide Variations between Financial Futures Initial Trade Price and Final Trade Price, Soybeans (CBOT), all prices in U.S.¢ per bushel.

Finally, the relationship between income, food price and consumption levels $C(I, S)$ is considered in detail in FAO (2011). Firstly, richer people consume more food. However, for the staple grains (corn, wheat and rice), this effect is minimal. The ‘income elasticity of grain consumption’ varies from +0.15 for low income groups to +0.05 for upper middle income groups, and for the high income group it actually falls (elasticity -0.01) since these people tend to eat more meat and less grains. However, meat consumption introduces a secondary effect. Richer people eat more meat, and those animals consume lots more grain. Income elasticities for meat are much higher, ranging from 0.31 to 0.68 across the income range, with the highest values in the middle-income groups (all figures from FAO’s own estimates (FAO 2011)).

Reviewing the key demand parameters, we observe that commodity prices themselves (S) introduce most uncertainty into long term agricultural demand predictions, since variations in S naturally affect the resulting consumption, $C(I, S)$.

Estimating Long Term Agricultural Supply

Detailed supply predictions need detailed agricultural data, such as the frequently updated Global Agro-ecological Zones (GAEZ) database (FAO/IIASA 2010) which identifies suitable locations for increased crop production through a high-resolution global database of soil, water, terrain and agro-climatic properties. Based on this, FAO (2011) predicts that total acreage of arable land will only grow 9% from 2005-2050 (it grew 14% from 1961-2005, a similar duration). In contrast, yields will have to rise 70-80% over a similar period if the FAO's own projections of agricultural demand are to be met. However, some studies report greatly higher predictions for acreage expansion, with global acreage more than doubling; Young (1999) argues that these are erroneous.

Predicting the Medium Term

In conclusion, significant uncertainties surround both agricultural demand and supply in the long term making long term scarcity hard to predict. In the short term (the 1-3 year timeframe) we have global inventories as a useful metric. Hoping to stimulate discussion of estimating agricultural scarcity in the medium term, we propose several measures of potential scarcity (say, occurring within the next 10 years) using only historical data.

Methods

Our proposed measures of potential scarcity, and a brief description of how we propose to estimate them, are described below.

Stocks-To-Use Ratio

We firstly report the widely quoted stocks-to-use ratio to examine whether its message agrees with that from other measures.

Market Concentration

It has long been recognised that situations of monopoly expose the consumer to price and/or disruption risk. High market concentration poses two risks to agricultural consumers. Firstly, political reasons may cause the sudden withdrawal of exports from a country either to maintain domestic supply (Russia, wheat, 2010) or, rarely, to 'punish' foreign countries (OPEC countries, oil, 1973). Secondly, if production is concentrated in few countries, unfavourable weather or natural disaster in a single producing country will greatly affect global supply.

We therefore test two measures of market concentration. Firstly we calculate the national concentration of global *production*. Secondly, we calculate the national concentration of global *exports*. When production is lower than expected, and despite potentially high international prices, countries typically first feed their own citizens out of obligation and political expediency, only exporting the remainder. A classic case is Russian wheat during its extreme drought of 2010, when production fell from 61 million tonnes (Mt) in 2009 to 41 Mt in 2010. Exports were banned for most of the year, allowing domestic consumption to continue almost unchanged, falling from 39Mt to 38Mt, while exports fell from 18Mt to 4Mt². Production that is destined for domestic consumption can thus justifiably be considered “off-limits” to the international market, supporting the argument for focusing on the market concentration of *exports*.

A number of well-known measures are available to measure market concentration. We use the Herfindahl-Hirschman index (Hirschman 1945; Herfindahl 1950). Possible values for this index range from 1.0 for a single monopolistic producer, down towards 0 for a situation with many small producers and no large producers. Although now mostly used to detect situations of excessive market concentration within a single economy (for example, U.S. merger law considers values above 0.25 to indicate ‘highly concentrated’ markets, (U.S. Department of Justice 2010)), Hirschman originally developed the index to detect the extent of national power in international trade, similar to our intended use.

Spare Capacity

Once the planting season is complete, this year’s crops are sown and little more can be done to increase total production apart from nurturing crops to maintain their yield. Yield has steadily risen globally over many years due to increases in technology, crop improvement, irrigation etc. It is nonetheless exposed to unpredictable weather, and thus varies widely at the national level. The overall crop production is the product of area *harvested* and the yield (computed as tonnes per harvested hectare in metric units). For a given crop year, there exists therefore no spare capacity in the system to grow more crops once the planting season is complete³.

² The apparent discrepancy in totals is due to drawdown of inventory.

³ This assumes all countries follow the same yearly planting cycle, clearly not the case due to multiple crops per year in some fertile regions, and also due to production in both North and South hemispheres. Nevertheless, as a first approximation we can say that acreage is fixed after planting.

For the following crop year, technology may allow a slight growth in the yield, but this is not guaranteed. The only way to ensure additional production is to plant additional acreage⁴. This can come (a) at the expense of acreage currently devoted to other crops ('substitution'), or perhaps used in the past but currently fallow or (b) by using land never previously allocated to crops, whether currently uncultivated grasslands, forest or currently allocated to livestock. We assume that method (b) can only take place slowly and incrementally – 'spare' land does not exist for long before it becomes used. We have developed a method to estimate the additional land available for acreage growth by method (a). For a given crop in a given country, we consider the *highest ever acreage* of that crop to be a good proxy for the maximum acreage *currently* attainable (i.e. able to be planted in the next crop). The extent to which this exceeds the currently planted acreage is therefore the *spare capacity*. We incorporate a fixed degradation rate (desertification, urban growth etc.) which may prevent us attaining a previous maximum acreage. A full mathematical derivation can be found in the appendix.

Having developed a technique for estimating agricultural spare capacity, we also validate its usefulness by examining the relationship between the price of a crop and its spare capacity.

Yield-at-risk

Yield varies from year to year, mainly as a result of weather but also due to other factors such as disease, the introduction of new technologies and the expansion of crop production into more marginal land. Global diversification of crop production means that, to some extent, global average yield is insulated from the variations in individual countries. We adapt the concept of 'value-at-risk' from finance to estimate 'yield-at-risk', measuring the likely degree to which yield may depart downwards from trend. This helps to put inventory values in perspective. If we hold 15% of annual production in inventory, but yield-at-risk is 10%, then clearly the inventory situation is less healthy than if yield-at-risk is only 2%.

Should we measure *yield-at-risk* or *production-at-risk*? Since acreage *planted* figures are unavailable for most countries worldwide, with only acreage *harvested* data being available, both measures have flaws. Measuring variations in yield, calculated based on *harvested* acres will not take into account years when conditions are so bad that crops are not

⁴ We used the widely used term 'acreage' meaning the area planted, although we use metric units of Hectares throughout.

even harvested. This is a significant flaw since we wish to focus on years when conditions are very poor. Measuring production at risk also has problems. Production varies because of the acreage planted, a manmade decision, as well as because of yield, subject to the random effects of weather and other influences. Measuring production at risk does not disentangle these factors.

The *value-at-risk* of a financial portfolio is defined at a certain confidence level. For example, the 95% daily value-at-risk of a portfolio is that (dollar) value which losses will not exceed on 95% of trading days. We construct a similar measure for yield, which we call *yield-at-risk*. Given that yields have been rising over the entire study period, we first predict a 'trend' yield for a given year. The extent to which actual yield falls above or below this value we term a 'surprise'. Naturally, only (large) negative surprises are a cause for concern, identically to the situation in financial markets, where a risk manager of an organisation is concerned mainly with large financial losses. In the domain of finance, value-at-risk can be estimated in two different ways.

Firstly, consider the case of measuring *daily* value-at-risk. We estimate from recent historical data the mean and volatility of daily returns. If returns are assumed to follow a normal distribution, or a similarly well-defined distribution, a closed form calculation for value-at-risk can be performed.

The second method makes no assumption for distribution of returns, but simply analyses historical data, with a weakness that a larger duration of historical data is needed. We simply look back in time and measure that loss that was only exceeded once every 20 days (for a 95% confidence level).

We employ both methods. For the first method, we assume a normal distribution for yields. Just and Weninger (1999) argue that disproving the normal distribution for agricultural yields is difficult. Even if farm- or area-level yields are non-normal, aggregating over large areas (as we do, globally), the central limit theorem will push aggregate yields towards a normal distribution, provided there are no global influences on crop yields (the weather phenomena of El Niño and La Niña might be such global influences). Following Yang et. al. (1992) we employ a GARCH(1,1) model to allow for heteroskedasticity in yield variations.

We calculate our yield-at-risk using the 90% confidence level, since yearly data gives us only a small number of data points. On average, a negative yield surprise should therefore

exceed our yield-at-risk value every 10 years (borrowing from value-at-risk terminology, we call this a ‘break’). We then use historical data to compare the empirical number of breaks with the theoretical value.

Land Competition

Farmers in many areas enjoy an “embedded optionality” in their choice of crop. Each year they can choose from several crops, subject to constraints such as soil quality, likely water availability, likely temperature range etc., available equipment and expertise etc. Typically this decision will be based on the respective crop prices, expected yields and possibly different input costs (fertilizer etc) with the crop with the higher expected profit being planted. For example, there is well documented competition between soybeans and corn in the U.S., with farmers keenly following the soybean-to-corn price ratio (Financial Times 2012). Other factors also affect decisions, such as the desire for diversification across several crops (Vavra and Colman 2003).

We use land competition as a sign of land scarcity. If ‘unused’ land is a plentiful resource then expansion of one crop is independent of other crops. Conversely, if little unused land remains, increased acreage in one crop must be at the expense of another crop. We measure this competition between pairs of crops, by calculating the correlation coefficient between their respective acreages (using different countries and years as separate data points). If we see a strong *negative* correlation coefficient, that is evidence of land competition. For details of the calculation see the appendix.

Having built a test for land competition between two crops, we then examine whether the results are consistent with *price* correlation between the various crops, since competition for land should elevate price correlation between two crops.

Data

Agricultural Production, Exports, Acreage

All data is sourced from the USDA’s ‘Production, Supply and Distribution Online’ database (USDA 2012). We consider the cases of wheat, soybeans, corn and rice. Yearly data from 1960 to 2011 is used, with each crop year allocated to the first of the two years involved

(hence crop year 2011/12 is allocated to 2011 for analysis purposes). We use data for all 139 countries available. We use USDA series for production, exports and harvested acreage. USDA publishes yield for some crops but not others, so we derive yield ourselves from production and harvested acreage.

Several issues arise allocating data to different countries due to the long time series. Only aggregate EU data is available for the 'EU-15' prior to 1999 and for the 'EU-27' afterwards; we therefore aggregate into a EU-27 for the full study period. USSR data was reported centrally until 1986, then split into the post-breakup countries afterwards; we keep this wherever possible reflecting the political reality of central control diversifying into individual decisions, apart from the case of calculating spare capacity for Soviet wheat, where the individual countries (especially Russia and Kazakhstan) are major exporters and we need an acreage history to perform the computation. In that case, we allocate the USSR's wheat totals prior to 1987 to its constituent post-breakup countries using the ratios of areas harvested in 1987. The breakups of Yugoslavia, Czechoslovakia, Sudan and Ethiopia are not material, nor the union of Germany (included under the EU-27 total) or the union of Yemen.

For acreage of other crops (other than the four which we study in detail), we use FAO's FAOSTAT database (FAO 2010) since its coverage of minor crops is more comprehensive.

Prices

Whilst recognising that agricultural prices for crops vary worldwide, we use a price series we believe to be reflective of a 'global' price for each crop, sourced from the World Bank "Global Economic Monitor – Commodities" database (World Bank 2012). All prices are in nominal US\$ per metric tonne; the database begins in 1960 and consists of monthly average prices. Specifically, we use the following series: Corn – Monthly Maize (U.S., No 2, yellow, f.o.b. U.S. Gulf ports); Rice – Monthly Rice, Thailand (5% broken, white rice, f.o.b. Bangkok); Wheat – Monthly U.S. Wheat (No 1, Hard Winter, export price at U.S. Gulf port); Soybeans – Monthly Soybeans (U.S., c.i.f. Rotterdam).

Where we have need for financial futures prices we use those prices from the CBOT exchange, downloaded via Datastream. Where necessary we deflate prices using the U.S. CPI index, downloaded via the "FRED" service (Federal Reserve Bank of St. Louis 2012).

Results

Background – The Major Crops and their Major Producers

Before our statistical analysis begins, we briefly describe the current world agricultural situation – what is grown and where.

Table 2 displays the major agricultural crops grown in terms of acreage, with both worldwide and U.S. acreage displayed (acreage harvested, in hectares), all figures from FAO (2010). It is clear that wheat, corn, rice and soybeans are the most important crops worldwide, and that, excluding rice, the same holds for the United States. This justifies our focus on these four crops.

Crop	World Acreage (Million Hectares)	U.S. Acreage (Million Hectares)	Crop	World Acreage (Million Hectares)	U.S. Acreage (Million Hectares)
Wheat	217.0	19.3	Sunflower	23.1	0.8
Corn ('Maize')	161.9	33.0	Potatoes	18.6	0.4
Rice	153.6	1.5	Cassava	18.4	-
Soybeans	102.4	31.0	Oil Palm	15.0	
Barley	47.9	1.0	Chickpeas	12.0	<0.1
Sorghum	40.5	1.9	Coconuts	11.7	-
Millet	35.1	0.1	Cow Peas	10.5	<0.1
Cotton	32.1	4.3	Coffee	10.2	<0.1
Rapeseed	31.7	0.6	Rubber	9.2	-
Beans, dry	29.9	0.7	Oats	9.0	0.5
Groundnuts	24.1	0.5	Cocoa	8.9	
Sugarcane	23.8	0.3			

Table 2 – Acreage of the World's Major Crops, 2010.

For the major four crops, we display in Table 3 the major producing countries, with their respective proportions of world production (measured in tonnage not acreage) and their respective proportions of total world exports⁵. The U.S. is a prominent producer, and even

⁵ Because tonnages and particularly exports vary significantly from year to year, we average the figures for the three years 2009, 2010 and 2011.

more dominant as an exporter. China and India are also major producers, but with large populations most of their production is for domestic consumption. Brazil and Argentina join the US as the dominant exporters of both corn and soybeans. Most rice is produced in and exported from Asia.

Crop	Major Producers (share of global production)	Major Exporters (share of global exports)
Corn	U.S. (38%), China (21%), EU (7%), Brazil (7%).	U.S. (49%), Argentina (16%), Brazil (11%), Ukraine (8%).
Wheat	EU (20%), China (17%), India (12%), U.S. (9%), Russia (8%), Australia (4%), Canada (4%).	U.S. (21%), EU (15%), Australia (13%), Canada (13%), Russia (10%), Argentina (6%), Kazakhstan (5%), Ukraine (4%).
Soybeans	U.S. (35%), Brazil (27%), Argentina (19%), China (6%), India (4%).	U.S. (42%), Brazil (34%), Argentina (11%), Paraguay (6%).
Rice	China (30%), India (21%), Indonesia (8%), Bangladesh (7%), Vietnam (6%), Thailand (5%).	Thailand (26%), Vietnam (21%), India (11%), Pakistan (11%), U.S. (10%).

Table 3 – Major Producing and Exporting Countries for the Four Major Crops, 2009-2011 Average.

Background : Acreage and Yield

Figure 1 shows the increase in acreage for all crops over the study period. In the case of wheat, global acreage has hardly changed; it has risen most sharply for soybeans. The USDA's coverage of soybeans began in 1964, hence the initial jump.

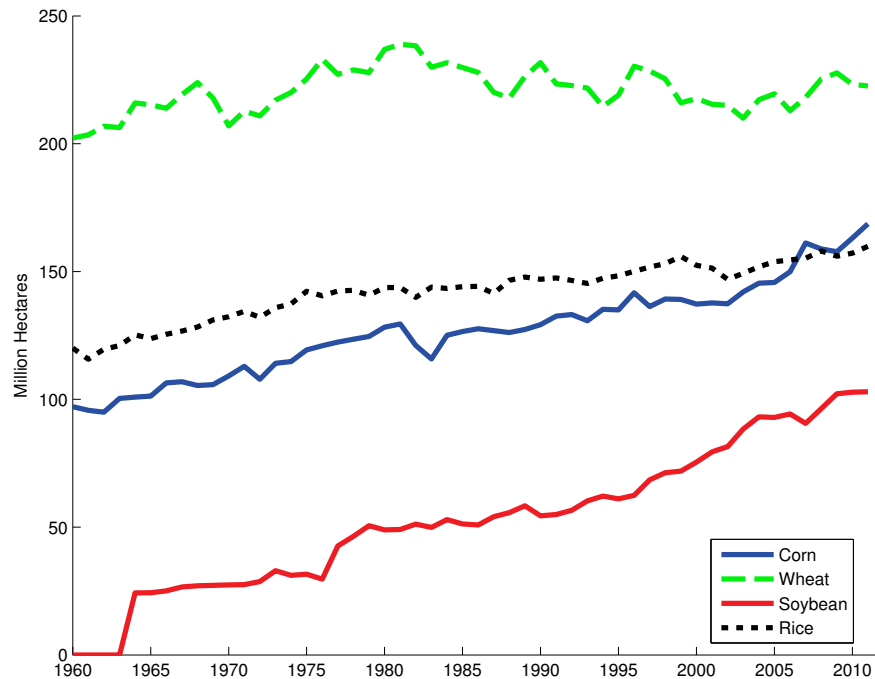


Figure 1 – Worldwide Harvested Acreage of the 4 crops, 1960-2011

Figure 2 shows the dramatic and consistent rise of global average yields for all crops. Yield growth was particularly marked for wheat up to 1990, allowing overall acreage to decline slightly. Yields are most consistent for rice and most variable for corn. The consistent quasi-linear trend for each yield, however, translates into a diminishing percentage growth rate over time. The higher yield for corn than other crops is balanced by the typically lower price per tonne; average prices per tonne during 2009-2011 were \$214 (corn), \$254 (wheat), \$475 (soybeans), and \$528 (rice)⁶. Yields vary widely between countries. Considering only the case of corn, 2011 yields for the major producers were 9.2 (U.S.), 5.7 (China), 7.3 (EU) and 4.0 (Brazil), with yields ranging from <1 in many least-developed countries up to 11 (Chile, New Zealand)⁷.

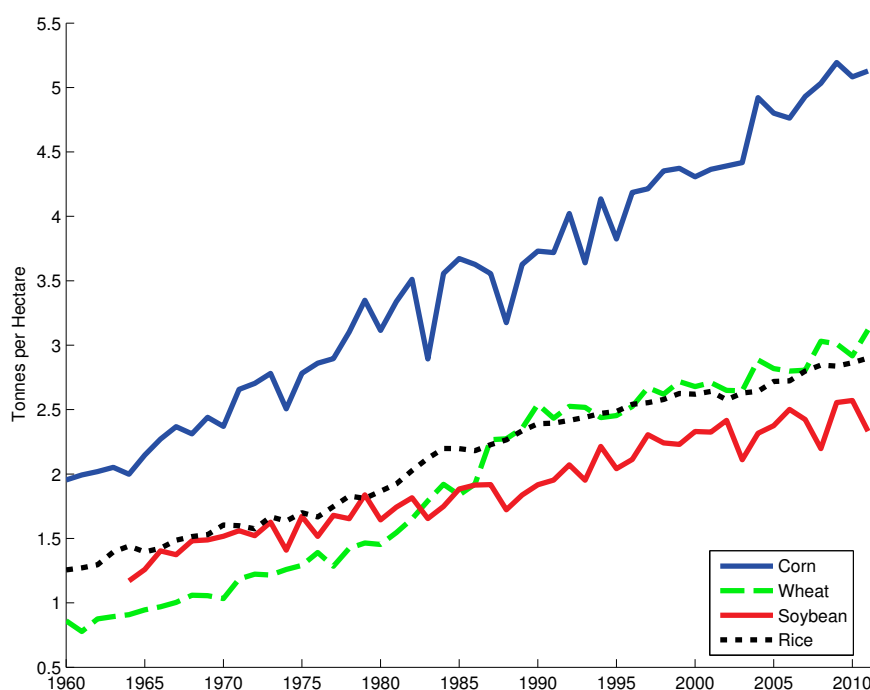


Figure 2 – Global Average Yield of the 4 crops in Tonnes per Hectare, 1960-2011.

⁶ All figures in nominal US dollars.

⁷ All figures in tonnes / hectare.

Stocks-To-Use Ratio

Figure 3 shows the evolution of the stocks-to-use ratio for each crop. This reflects the worldwide inventory⁸ remaining shortly before the beginning of the new harvest, expressed as a percentage of worldwide annual consumption. Apart from soybeans, recent years show a marked decline in the ratio from the abundant peaks reached in the 1985-2000 period. Many blamed the subsequent 2006-2008 agricultural price spike on these fundamentals (FAO 2007), with high demand depleting inventory and triggering high prices. Dissenters include Headey and Fan (2008) and Dawe (2009) who attribute high prices instead to higher agricultural energy costs and the growth of biofuels. Considering the present situation, corn inventories are currently the lowest, with wheat relatively plentiful. The FAO has previously labelled 17-18% stocks-to-use as the minimum ratio “necessary to safeguard world food security” (FAO 1996); corn is currently below this level.

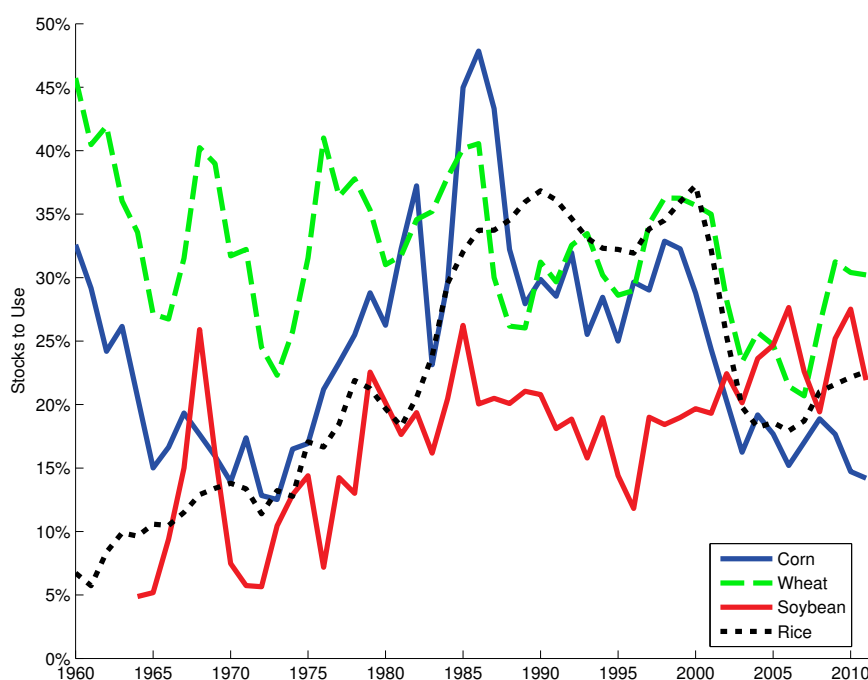


Figure 3 – The Stocks-To-Use Ratio of the 4 Crops, 1960-2011.

⁸ We use the word ‘inventory’ in preference to ‘stocks’ since the latter introduces confusion with equity markets. We retain the term ‘stocks-to-use ratio’ since this term is widely used in the agricultural commodity literature and by the USDA.

Market Concentration Measures

We display in Figure 4 the market concentration index for the production of each crop. Recall that values close to 0.0 represents numerous small producers, and 1.0 represents monopoly. Diversification has increased over the study period, and is especially pronounced for wheat, where no country now exceeds 20% of global production. The higher values in earlier years are not due to missing data – almost all countries report production figures right back to 1960. The reduction of market concentration in soybeans is particularly marked. Although remaining the least diversified (the U.S., Brazil and Argentina produced over 80% of the world's total in 2009-2011), the figure has dropped hugely from the relative monopoly enjoyed by the U.S. prior to 1977, mainly due to Brazil's entry and rapid production ramp in the period 1977 to 1984.

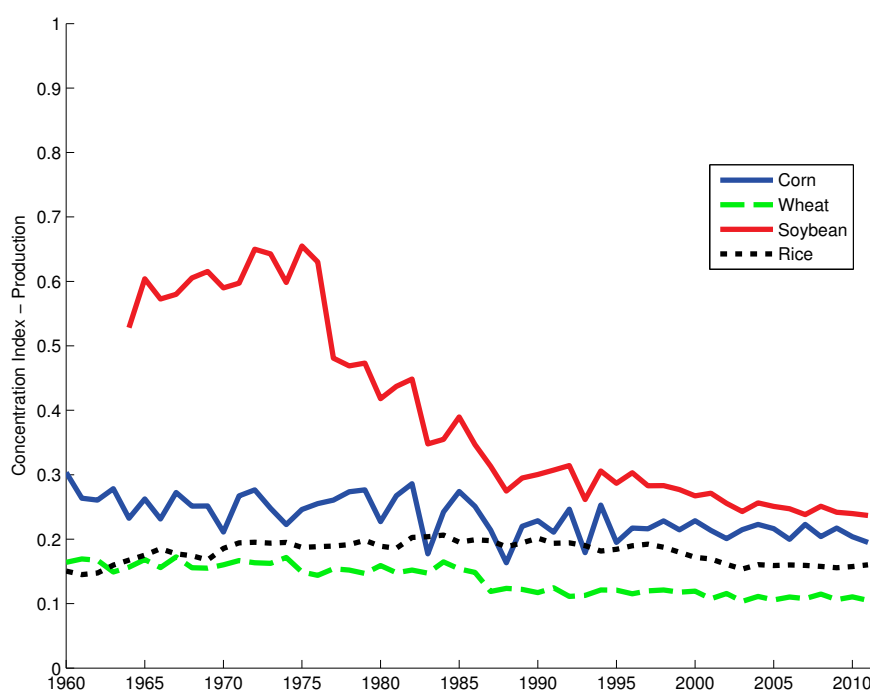


Figure 4 – Market Concentration of Production, 1960-2011

Figure 5 shows the corresponding market concentration index for *exports*. Note the higher market concentration for exports than for production, since many countries produce sufficient for domestic demand but export little. A clear split emerges – soybeans and corn remain relatively concentrated, whereas rice and wheat are more diversified. Currently (average of 2009-2011 crops), 49% of global corn exports come from the U.S. alone, with Argentina, Brazil and Ukraine contributing 8-16% each. No other country contributes more than 2%. For soybeans, Brazil and the U.S. dominate, with 42% and 34% of global exports respectively. Argentina and Paraguay trail with 11%, and 6% respectively, with barely any exports from elsewhere.

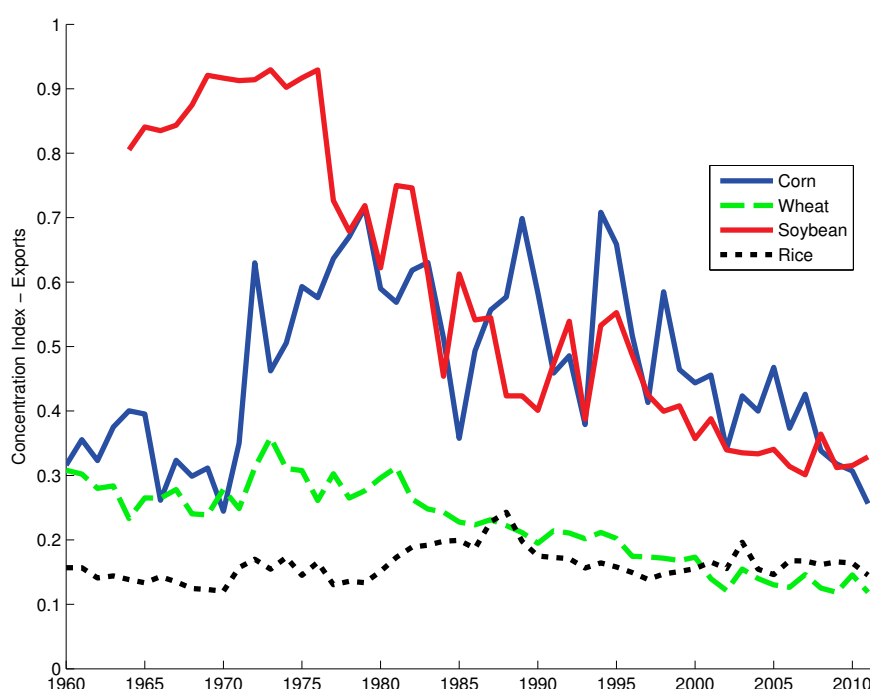


Figure 5 –Market Concentration of Exports, 1960-2011

In summary, market concentration has decreased over the years, and continues to decrease, which is definitely good news for the consumer, giving reduced risk of scarcity. However corn and soybeans can still be considered concentrated markets, with consumers vulnerable since the US, Brazil and Argentina are the only significant exporters of these crops.

Spare Capacity

We now turn to spare capacity. We use a novel methodology to estimate worldwide spare capacity for each crop, as described in the Appendix. The values we compute, for each crop and for each year since 1960 are plotted in Figure 6. Note that when we speak of capacity, we are talking about acreage, so spare capacity is the ability to plant *additional*

acreage, and we represent this as a percentage of the current acreage. Values for early years should be viewed with caution, since our calculation needs historical data prior to a given year to estimate the spare capacity in that year. The graph is 'spiky' – a peak of spare capacity can emerge in 1-2 years and be absorbed quickly by acreage growth. Wheat notably has the highest spare capacity. Figure 1 reminds us that wheat acreage has barely grown from 1960 to 2011, with acreage increasing in some countries and falling elsewhere, leaving significant spare capacity. Aside from wheat, spare capacity is falling to historic lows last observed in 1980. Corn enjoyed a spare capacity peak of around 8-10% until 2002, dropping to around 4% now. Soybeans saw a similar trend but with an earlier drop. Rice spare capacity has remained lowest but relatively static in the region of 3%-4% since 1980, perhaps related to the smooth growth in acreage, Figure 1.

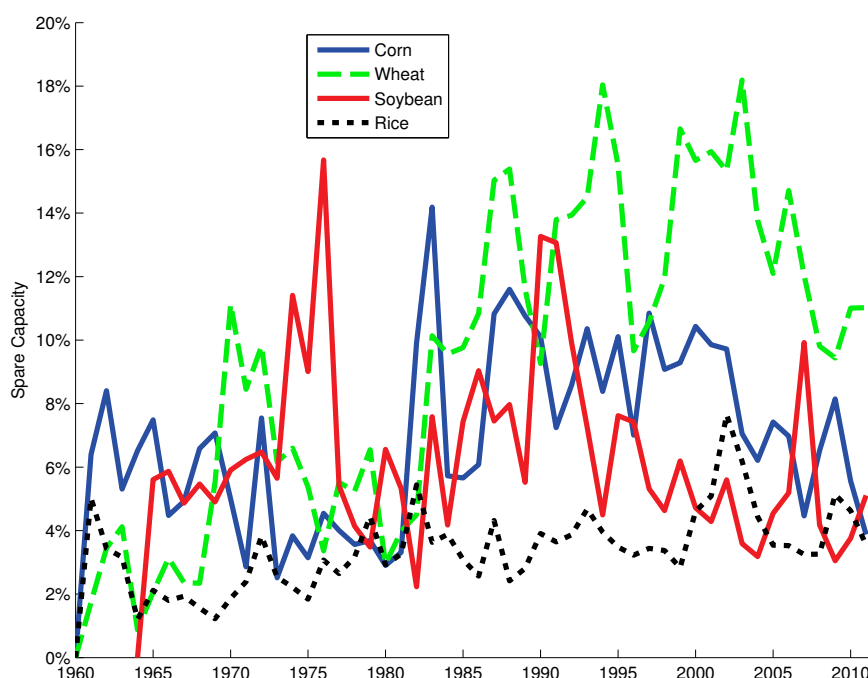


Figure 6 – Our Metric of “Spare Capacity” Measured Worldwide for Each Crop, 1960-2011.

Where does this global spare capacity lie? We list in Table 4 the largest four contributors to current spare capacity for each crop, listing their current acreage and their best acreage⁹ achieved and in which year this occurred, as well as the discounted value of this best acreage .

Notable are the large spare capacity numbers for wheat compared to the other crops. We also see a range of dates for the ‘year of best acreage’, however values around the early

⁹ See the appendix for details and the definition of ‘best acreage’.

1990's seem to predominate. This perhaps supports slightly increasing the discount rate 'd'; if we have not been able to exceed acreage from 1990 in a particular country in the intervening 21 years to 2011, is it really possible that we could achieve this in the 2012 crop year?

Nevertheless, the discounting factor somewhat takes this into account – consider the Philippines, where 3.86 million hectares of corn grew in 1990, versus 2.58 million today, a drop of 1.28 million hectares, yet we claim only 0.54 million hectares of spare capacity. This would require only 42% of former corn-growing land to be replanted with corn.

Figures in Million Hectares						
Crop	Country	Year of Best Acreage	Best Acreage	Best Acreage Discounted to 2011	Current Acreage	Spare Capacity in 2011
Corn	Mexico	2004	7.69	7.17	6.00	1.17
	South Africa	1986	5.06	3.94	3.20	0.74
	Thailand	1985	2.27	1.75	1.01	0.74
	Philippines	1990	3.86	3.13	2.59	0.54
Wheat	US	1981	32.62	24.17	18.50	5.67
	Canada	1991	14.16	11.59	8.55	3.04
	Russia	2009	28.70	28.13	25.55	2.58
	China	1998	29.77	26.14	24.20	1.94
Soybeans	China	2005	9.59	9.03	7.65	1.38
	US	2010	31.00	30.69	29.80	0.89
	Indonesia	1991	1.56	1.27	0.46	0.81
	Italy	1990	0.52	0.42	0.00	0.42
Rice	Brazil	1979	6.47	4.70	2.50	2.20
	Japan	1969	3.27	2.15	1.58	0.57
	Myanmar	2010	7.00	6.93	6.50	0.43
	US	2010	1.46	1.44	1.06	0.39

Table 4 – Countries Possessing the Greatest Spare Capacity for Each Crop, Measured in 2011

Ideally, for spare capacity we would like to have data down to the resolution of individual farms, or even individual fields. For example, if a field has previously grown soybeans, it probably has the capability to grow soybeans again. There are several reasons this might not be the case:

- Urbanisation – the field is permanently removed from agricultural use
- Desertification or unavailability of water for irrigation
- Other reduction in land quality (erosion, depletion of nutrients etc.) sufficient to make a crop untenable
- Climate change sufficient to render the crop no longer suitable for the area
- A diminishing of agricultural knowledge on the farm necessary to grow the crop
- Lack or degradation of agricultural equipment or other infrastructure necessary for the specific crop.

Since we typically only have acreage values at the national level, our measure of spare capacity is clearly only an approximation, and our ‘decay rate’ of 1% p.a. applied at the national level to the ‘best acreage’ (see Appendix) aims to absorb those reasons above.

In the case of the U.S., we also have state-level acreage data. We therefore also studied spare capacity for the U.S. itself in isolation (i.e. considering only acreage and consumption within the United States). With higher resolution data, we found it necessary to change the spare capacity annual ‘decay rate’ to 3%¹⁰. This produces the evolution of U.S. spare capacity in Figure 7. We see a more ‘jumpy’ graph – it is possible for most of a large spare capacity to be absorbed in a single year, as we would expect (consider the case of corn in the early 1980’s). It is possible that at a national level, farmers tend to behave homogenously, since they are all observing similar national prices. Globally, farmers behave more heterogeneously, exposed to differing regional costs, weather issues and political and logistical

¹⁰ We manually ‘tuned’ the decay rate in both the worldwide (country level data) and the US-centric (state level data) cases to 1% and 3% respectively. On the one hand, a decay rate of 0 tends to produce spare capacity that grows and grows (i.e. non-stationarity) since we ignore those effects which render land permanently unsuitable for a crop it once grew. On the other hand, with too high a decay rate, we never observe spare capacity building, and instead experience acreage growth “surprises”. For example, if acreage drops by 5% in one year, and our decay rate is 5%, we have not ‘created’ any spare capacity, yet we may suddenly see acreage ‘unexpectedly’ increase by 5% the next year.

pressures and constraints. Therefore globally spare capacity varies relatively slowly. Results from the U.S.-centric data are similar to those at worldwide level; spare capacity of corn and soybeans is low at around 4%, near historic lows, whereas wheat enjoys much higher spare capacity.

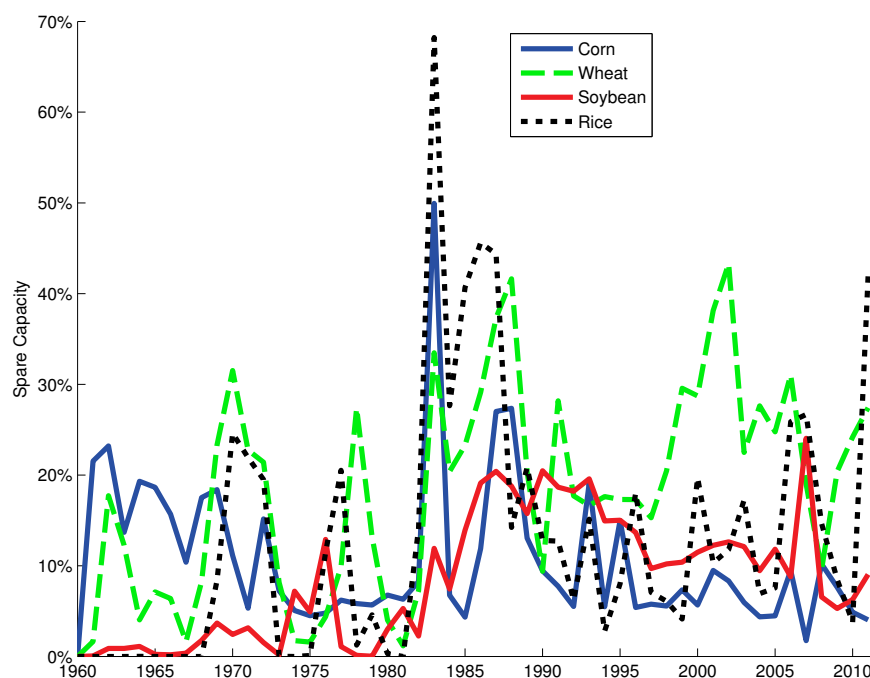


Figure 7 – Our Metric of “Spare Capacity” Measured Solely in the U.S. for Each Crop, 1960-2011.

The Relationship between Price and Spare Capacity

In order to validate our spare capacity values, we examine whether a relationship exists between price and spare capacity. The relationship between the price of an agricultural commodity and its *inventory* is well known, we will review this first. Working (1933; 1949) first developed the “Theory of Storage” by studying wheat prices. He showed that in times of scarcity (measured as unusually low inventory before the harvest), futures prices for delivery shortly before the harvest (when scarcity was most pronounced) greatly exceeded prices for delivery after the harvest. In periods of abundance, there was little difference in the pre- and post- harvest price.

Rather than measure the slope in futures prices, as already conducted by Brennan (1958), Telser (1958) and more recently Geman and Nguyen (2005), we choose to examine *absolute* prices. In part, this is because futures markets have not existed for all four crops over the entire study period. Further, absolute crop prices are relevant to a wider audience than

the price *change* predicted by futures prices. We use monthly average prices from the World Bank's Global Economic Monitor Database (World Bank 2012), deflated using the U.S. CPI index and represented in 2012 U.S. dollars.

The relationship between *inventory* and price

First let us review the well-known relationship between inventory and price. In Figure 8(a) to (d) we display in scattergram form the relationship between price (observed in January after the harvest, and deflated) and the worldwide stocks-to-use ratio. We group decades in different colours, and break the period between 2000 to 2011 into several groups.

In each case, a visible but not strong relationship can be seen of the form expected (low inventory = higher price). Prices for the most recent years (2005-2008 and 2009-2011) are consistent with the long-term pattern, building an argument that the 'high' prices for crops observed recently are due to the fundamental factor of scarcity rather than due to speculation.

In Table 5 we display this relationship numerically using the Spearman (1904) correlation coefficient¹¹. The values confirm the relationship, except in the case of wheat. Unlike the other crops, the stocks-to-use ratio for wheat has never fallen below 20%. The weak relationship for wheat may be because wheat has never been particularly scarce and so we do not observe a full curve from high to low inventory values.

	Corn	Wheat	Soybeans	Rice
Spearman Correlation Coefficient	-0.467	-0.039	-0.491	-0.628

Table 5 – Strength of the Relationship between Deflated Crop Price (January Average Subsequent to the Crop Harvest) and the Worldwide Stocks-to-use Ratio, Yearly Samples, 1960-2011.

¹¹ Rather than use the usual (Pearson) correlation coefficient to determine the strength of the relationship, we note the non-linearity with rapidly increasing prices during extreme scarcity, and use the Spearman (1904) correlation coefficient. Essentially, the Spearman coefficient is the same as the Pearson coefficient, but first the x and y values are ranked, and the Pearson coefficient of the ranks then calculated. Identically to the Pearson coefficient, the Spearman coefficient lies in [-1,1] with negative values indicating an inverse relationship.

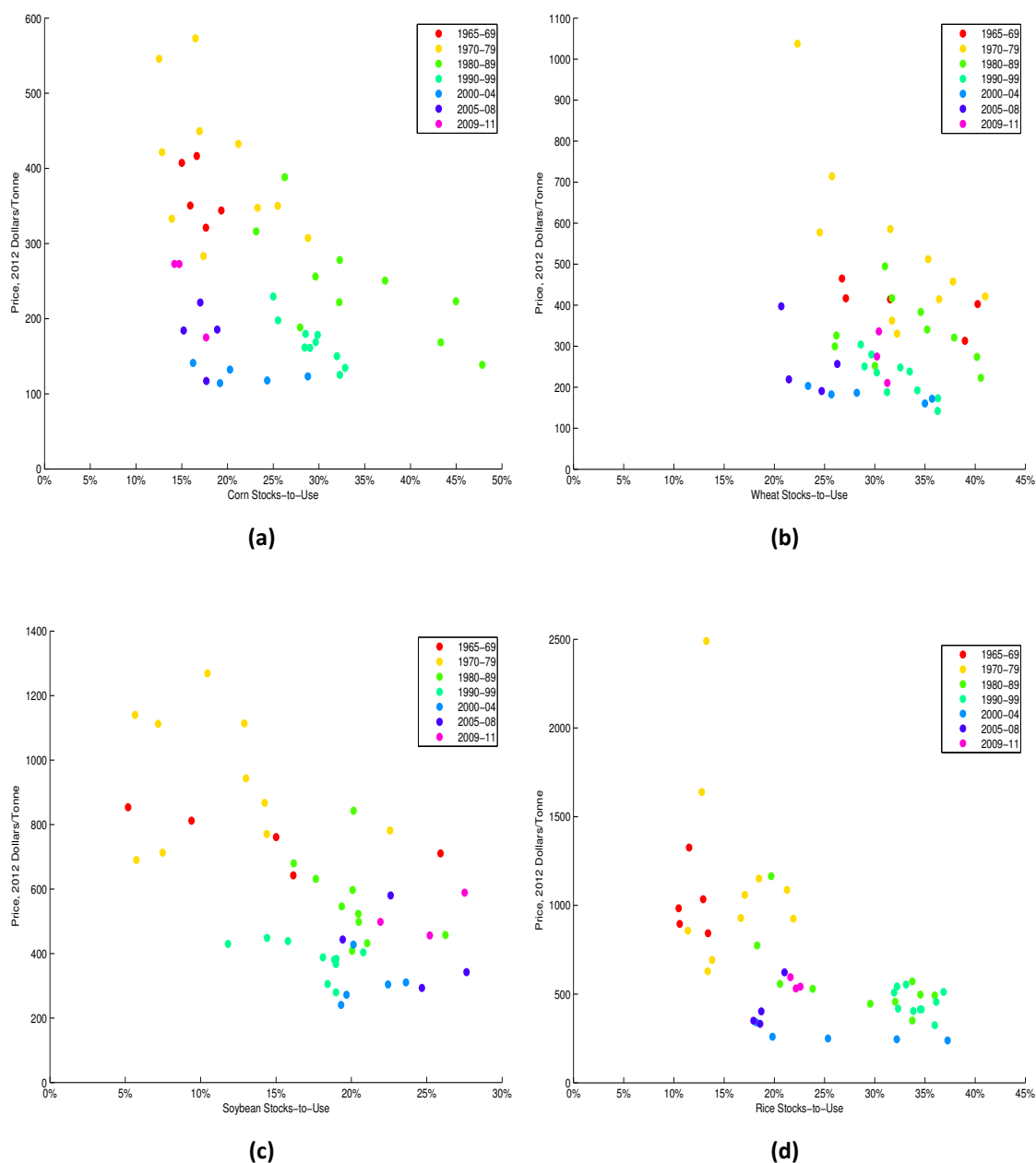


Figure 8 - The Relationship between Crop Price and the Stocks-To-Use Ratio for (a) corn, (b) wheat, (c) soybeans and (d) rice respectively. Price is January average following the harvest year. Stocks-to-use is global.

The relationship between *spare capacity* and price

We now examine the relationship between *spare capacity* and price, with spare capacity estimated, as previously described, on a global basis¹². In this case we compare the worldwide spare capacity with the average (deflated) price observed during January *of the harvest year*¹³. We observe a strong relationship for corn, wheat and rice, see Figure 9. Only for soybeans is the relationship not visible. The Spearman correlation coefficients are listed in Table 6.

We also list the Spearman correlation between deflated price and *U.S.* spare capacity in Table 6. The strong relationship is now also apparent for soybeans, but weaker for corn. In general, the relationship between *spare capacity* and price (Table 6) is stronger than the widely cited relationship between *inventory* and price (Table 5).

Spearman Correlation Coefficient	Corn	Wheat	Soybeans	Rice
Worldwide data	-0.663	-0.880	+0.049	-0.592
U.S. data	-0.035	-0.725	-0.698	-0.475

Table 6 - Strength of the Relationship between Deflated Crop Price (January Average of the Crop Harvest) and the Spare Capacity Statistic (both Worldwide and U.S.), Yearly Samples, 1965-2011.

¹² We omit the years 1960-1964 to allow the spare capacity metric, which depends on several years of historical data, to calibrate.

¹³ We found the relationship between price and spare capacity peaked shortly before the planting season.

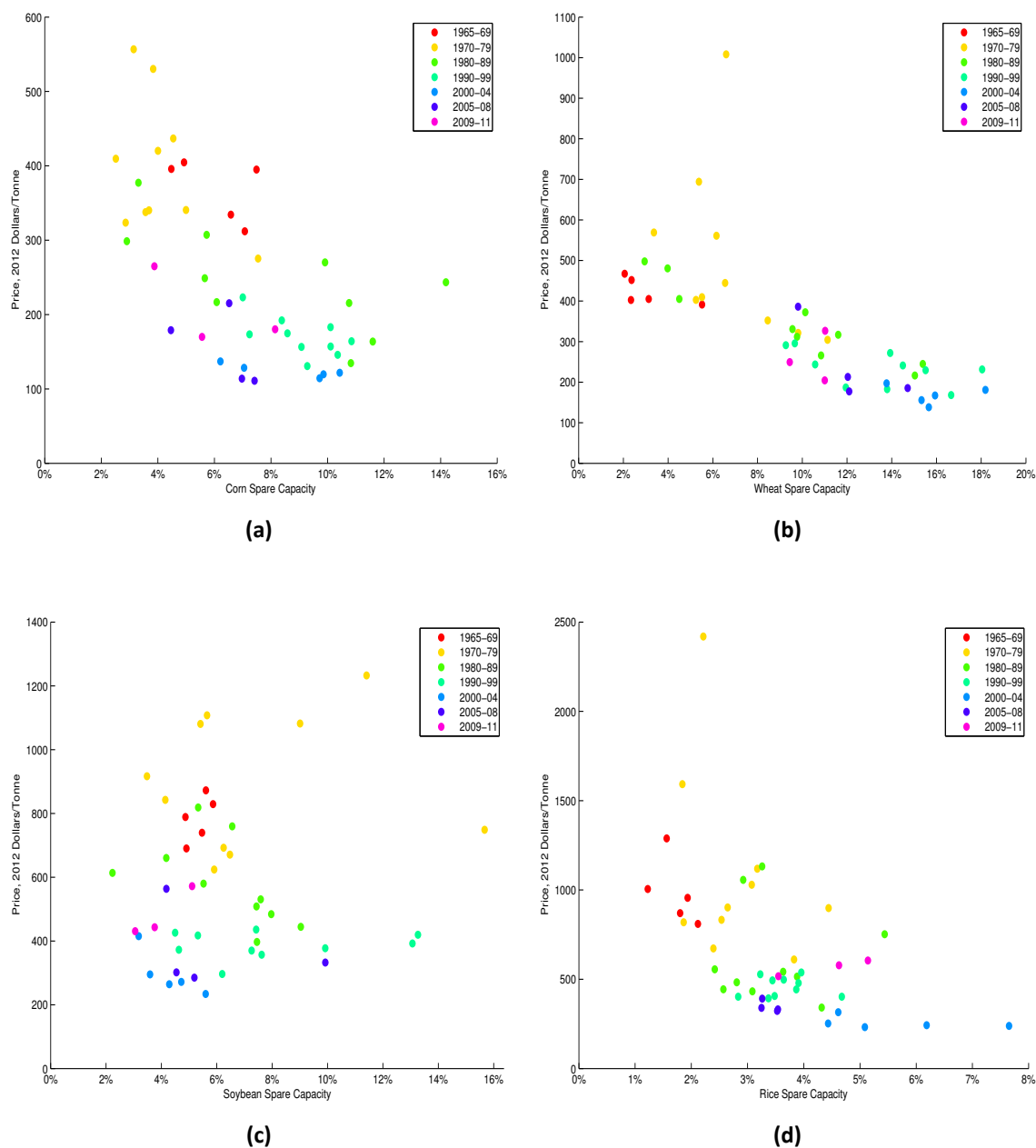


Figure 9 - The Relationship between Crop price and *Spare Capacity* for (a) corn, (b) wheat, (c) soybeans and (d) rice respectively. Price is January average of the harvest year. Spare capacity is global.

Yield-at-risk

To study variations in yield, the identification of trend is crucially important (Just and Weninger 1999). Our methodology for calculating a trend is described in the Appendix. We display in Figure 10 our calculated trend-line for wheat yield, as well as the observed yields. Visually, our trendline gives a good fit, neither jumpy (over-fitted) nor failing to capture the broad trends (underfitting). The curve also fits the end-periods relatively well. The trend-lines for the other crops performed similarly.

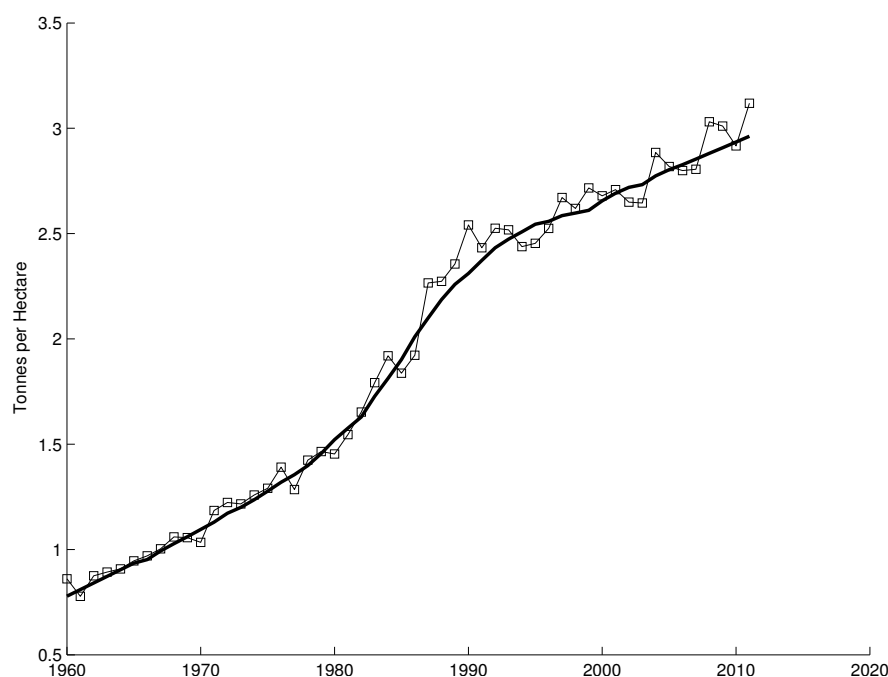


Figure 10 – Calculated Trend Yield and Actual Yield for Wheat, 1960-2011

**The thin line with the square data points represents actual yield,
while the thick continuous line is the trend-line.**

In Figure 11 we display for each crop a histogram of yield ‘surprise’, i.e. deviation from the trend, measured as a percentage under or over the predicted (trend) value. Also displayed is the 90% yield-at-risk value calculated from the GARCH model (continuous line). A yield-at-risk ‘break’ therefore occurs when a histogram value descends below the continuous yield-at-risk line. Note that the y-axes differ between crops. We display also summary data for the 4 crops in Table 7.

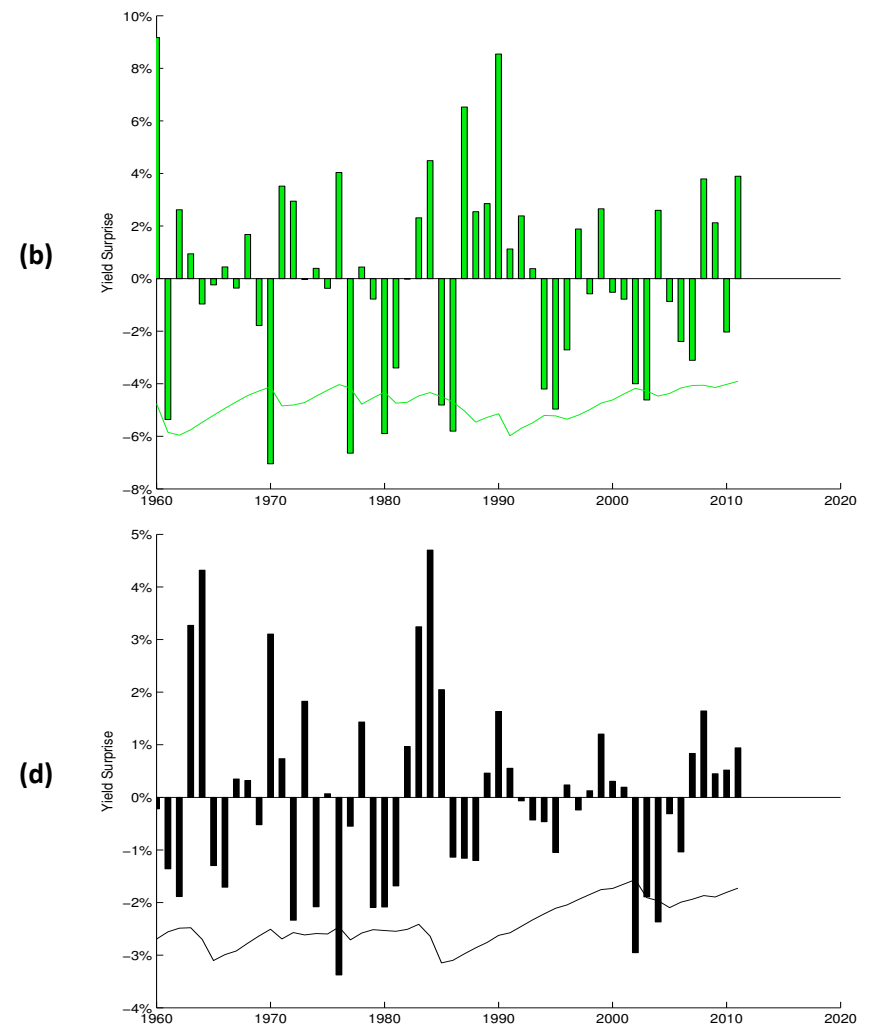
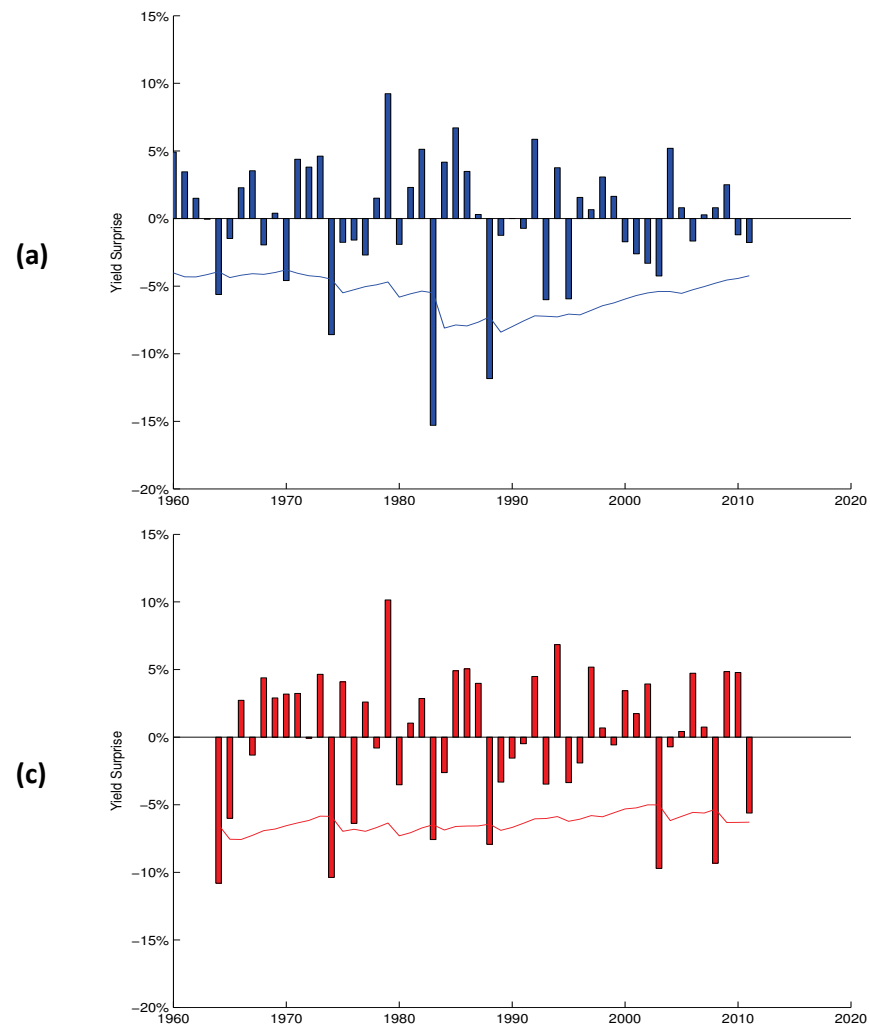


Figure 11 – Actual Yield Surprise (Histogram) and our Yield-at-Risk Estimate (continuous line) for (a) corn (b) wheat (c) soybeans and (d) rice.

Crop	Number of Data Points (Years)	1-Lag Auto-correlation of Yield Surprise	Kurtosis of Yield Surprise	2011 Yield-at-risk (90% level)	Number of Break Years	Expected Number of Break Years
Corn	52	-0.130	4.71	-4.2%	5	5.2
Wheat	52	-0.013	2.87	-3.9%	6	5.2
Soybeans	48	-0.186	2.54	-6.3%	6	4.8
Rice	52	0.278	3.20	-1.7%	3	5.2

Table 7 – Results of the Yield-at-Risk Calculation using a GARCH Model

We see for all crops no clear trend in positive or negative surprises. There are no long periods of positive or negative surprise (which might indicate an under-fitted trendline). This is statistically confirmed by the 1-lag autocorrelations of surprise being close to 0 for all crops.

The kurtosis of yield surprise for each crop is close to 3 (as for a normal distribution) in all cases except corn, which displays moderate excess kurtosis, pointing to greater extreme changes than would be expected by a normal distribution.

Yield-at-risk (the solid line in each graph) shows moderately constant yield-at-risk in most cases, with a slight fall in recent years. Our chosen GARCH parameters allow yield-at-risk to decline only slowly in the presence of reduced surprises. Corn shows a marked increase in yield-at-risk during the 1980's, when two major droughts (1983 and 1988) decimated corn-growing areas.

In order to validate whether our yield-at-risk model is reasonable, we also display in Table 7 the number of years in which actual yield surprise exceeded the yield-at-risk value (on the negative side), so called 'breaks'. Since we calculate the 90% confidence level yield-at-risk, a break should occur once every 10 years. For all crops, breaks actually occurred between 3 and 6 times, versus the expectation of 5.2 times (corn, wheat, rice) and 4.8 times (soybeans, due to the shorter sample period). Using the binomial distribution, we can calculate the probability of exactly $K = k$ breaks in a sample of n years, given a probability $p = 10\%$ of a break in each year as:

$$\Pr(K = k) = \frac{n!}{k!(n-k)!} p^k (1-p)^{n-k} \quad (1)$$

We display the results of this computation in Table 8. Due to the relatively low sample sizes, the probability mass is quite widely distributed. Our observed breaks of 3 to 6 years lie firmly in the central region of probability mass, supporting our yield-at-risk estimates.

Probability of observing exactly k breaks											
Crop	k:	1	2	3	4	5	6	7	8	9	10
Corn,											
Wheat,		2.4%	6.8%	12.7%	17.2%	18.4%	16.0%	11.7%	7.3%	4.0%	1.9%
Rice											
Soybeans		3.4%	8.9%	15.1%	18.9%	18.5%	14.7%	9.8%	5.6%	2.8%	1.2%

Table 8 - Probability of Observing Different Number of Yield-at-Risk Breaks over the Study Period

Finally, we now compare the most recent yield-at-risk for each crop most recent stocks-to-use ratio, see Table 9. These are directly comparable if we assume that trend yield growth has historically allowed supply to match demand. A (global) yield surprise of -10% would cause a stock drawdown equivalent to 10% of global demand. We can therefore divide the stocks-to-use ratio by the yield-at-risk, to obtain what we term the ‘yield-at-risk coverage duration’. We can think of this as the number of successive bad crops (at the 90% level) that would completely empty inventories. Not only does corn currently have low inventories, but the high yield-at-risk gives a coverage duration of only 3.4 years. For soybeans, the picture is equally bad; its higher inventories are matched by a higher yield-at-risk. Wheat is relatively plentiful, with almost 8 years of coverage, and rice is the most plentiful, with over 13 years of coverage, mainly because the yield-at-risk of rice is substantially lower than the other crops (also clearly visible in Figure 2).

Crop	2011 Yield-at-Risk (90% level)	2011 Stocks-to-Use Ratio	Yield-at-Risk coverage Duration
Corn	-4.2%	14.2%	3.4
Wheat	-3.8%	30.2%	7.9
Soybeans	-6.3%	21.9%	3.5
Rice	-1.7%	22.6%	13.3

Table 9 – Comparison of Yield-at-Risk and the Stocks-to-Use Ratio for each Crop.

Land Competition

In order to look for evidence of competition for land between the four crops, we plot in Figure 12 the pairwise correlation coefficient between the yearly changes in acreage, measured over several years and for the main producing countries (for details of the calculation see the Appendix). In other words, do acreages of the two crops rise together (correlation close to 1), are they independent (correlation close to 0) or is there land competition, with acreage growth in one crop corresponding to acreage fall in the other (correlation close to -1)? A medium-thick line represents a correlation that is statistically non-zero at the 5% confidence level, and a very thick line similarly at the 1% confidence level.

Firstly we notice that between most crop pairs, and for most years, there has been low correlation (thin lines). There was a period from approximately 1982 to 1990 where there was strong positive correlation between acreage change in corn, wheat and soybeans. This interesting result is not immediately apparent from viewing the raw world acreage chart earlier (Figure 1).

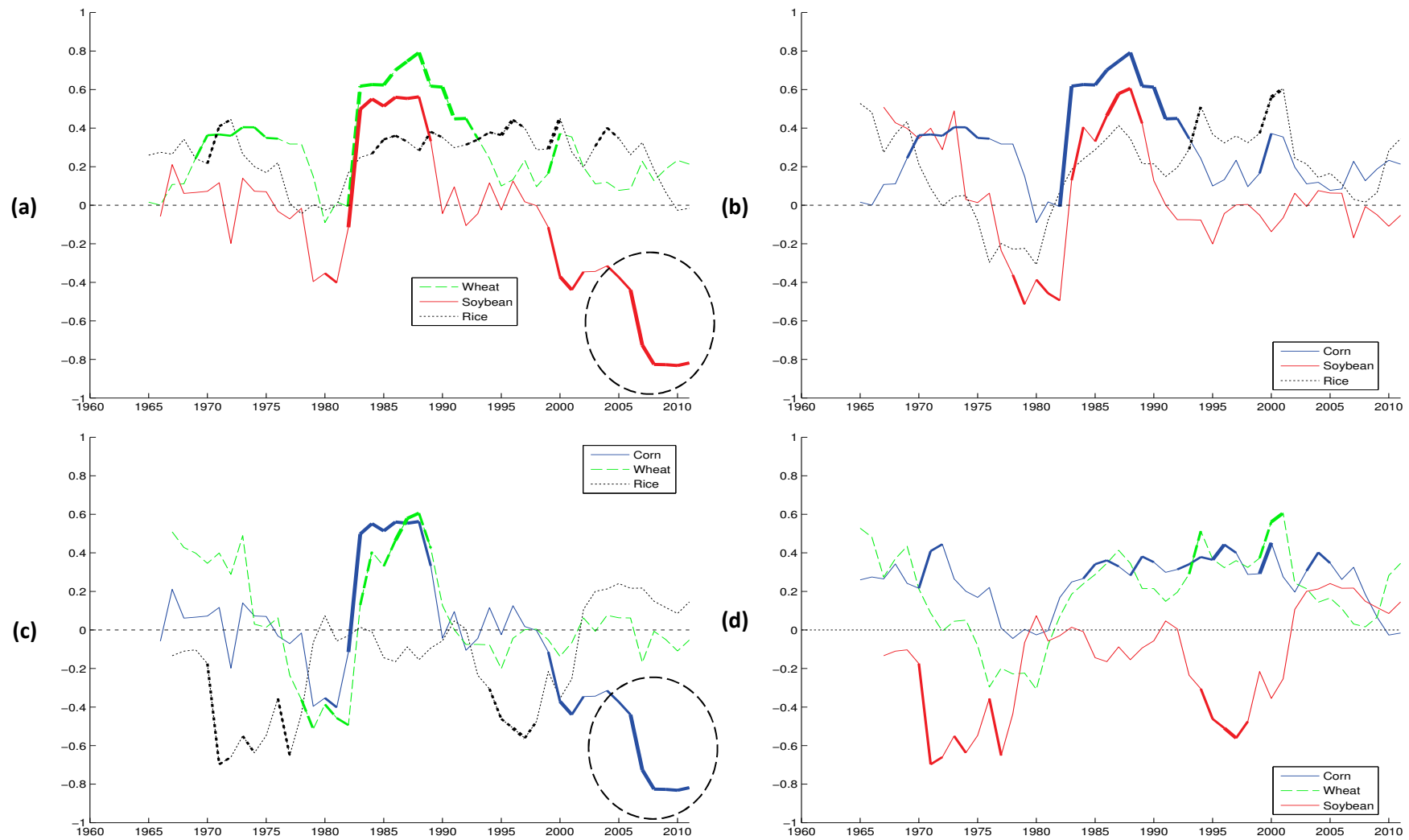


Figure 12 - Correlation Coefficient in Acreage Change between (a) Corn, (b) Wheat, (c) Soybeans and (d) Rice, Respectively, and the *Other 3 Crops* (hence each pairwise correlation is displayed in 2 different graphs).

Year	Correlation Coefficient	Year	Correlation Coefficient
1998	-0.002	2005	-0.373 *
1999	-0.114	2006	-0.440 *
2000	-0.371 *	2007	-0.726 **
2001	-0.439 **	2008	-0.826 **
2002	-0.346 *	2009	-0.827 **
2003	-0.343	2010	-0.832 **
2004	-0.315	2011	-0.818 **

Table 10 – Correlation between Changes in Acreage in Corn and Soybeans, Major Producing Countries.

*** and ** represent statistically significant non-zero correlations at 5% and 1% confidence levels respectively.**

More importantly, there appears to be, from around 2000 onwards, a growing inverse correlation between acreage of corn and soybeans (visible in Figure 12(a) and 12(c), and circled on the chart for emphasis). The raw correlation values are listed in Table 10. Moderate (negative) correlation emerges around 2000, with the effect strengthening from 2007 onwards.

To understand the source of this correlation, Table 11 lists the 2009-2010 and 2010-2011 changes in corn and soybeans acreage (the most recent data available) for the largest producers. For each country, we also list the annualised increase in the total crop acreage (for all 4 crops) measured over the period 2000-2011 to help us understand how fast total acreage is growing. Instances of land competition in a particular year (simply defined as growth in one acreage concurrent with fall in the other) are marked in bold.

Country	Change in Acreage (Million Hectares)				Yearly Total Acreage Growth
	2009-2010		2010-2011		2000-2011
	Corn	Soybeans	Corn	Soybeans	Corn + Wheat + Soybeans + Rice
U.S.	+0.8	+0.1	-1.2	+1.0	0.2%
China	+1.3	-0.7	+0.9	-0.9	0.6%
EU	-0.3	+0.1	+0.8	-	-0.2%
India	+0.3	-0.3	+0.1	+1.0	1.0%
Brazil	+0.9	+0.7	+1.5	+0.8	3.3%
Argentina	+0.7	-0.3	+0.1	+0.3	3.0%
Ukraine	+0.6	+0.4	+0.8	+0.1	5.1%

Table 11 – Acreage Changes from 2009-2010 and from 2010-2011, Corn vs Soybeans, Major Producers.
Evidence of land competition is marked in bold.

We can split the countries in Table 11 into two distinct groups. Firstly are the low-acreage growth countries ($\leq 1\%$ p.a.), consisting of the U.S., China, EU and India. In each of these countries we see evidence of corn-soybean land competition in either 2009-2010, 2010-2011 or both, with the case of China being particularly pronounced. In the second group of countries (Brazil, Argentina, Ukraine) we see rapid growth in total acreage of at least 3% p.a., and little evidence for land competition, with acreage for both crops rising in both periods (a single exception being Argentina with one period showing possible land competition).

Does Price Correlation Support the Theory of Land Competition?

Since we observe land competition between corn and soybeans emerging since around 2000, but not in other crop pairs or at other times, we tested whether price correlation supports this. One factor causing price correlation between commodities is competition for some resource needed to produce the commodity (or move, extract, refine it, etc.) In our case, if soybeans and corn are competing for the same land, this should increase their price correlation. To study this, we list in Table 12(a) and (b) the correlation in monthly prices¹⁴ between the four crops over two sub-periods, 1960-1999 and 2000-2011.

(a)	Correlation (1960-1999)	Corn	Wheat	Soybeans	Rice
	Corn	1	0.41	0.54	0.09
	Wheat		1	0.25	0.11
	Soybeans			1	-0.11
	Rice				1

(b)	Correlation (2000-2011)	Corn	Wheat	Soybeans	Rice
	Corn	1	0.46	0.61	0.16
	Wheat		1	0.45	-0.01
	Soybeans			1	0.13
	Rice				1

Table 12 - Pairwise Correlation Coefficient between the Monthly Price Returns of the Four Crops, for (a) 1960-1999, N=479 (b) 2000-2011, N=143

Examining Table 12 shows that the price of rice is almost uncorrelated to other crops, even in the more recent period. The other three crops (corn, wheat, soybeans) show moderate correlation as a group, with the strongest correlation between corn and soybeans,

¹⁴ Strictly speaking, it is the correlation between price *returns*.

supporting the theory of land competition. Excepting rice, all correlations have risen since 2000. Emerging land competition between corn and soybeans cannot therefore be the sole reason for increasing price correlation.

Conclusion

We have reviewed both traditional and novel measures of agricultural scarcity in the four major crops. Since 1960, moderate increases in planted acreage have combined with impressive gains in yield to greatly increase global production.

The traditional measure of agricultural scarcity, the 'stocks-to-use' ratio shows some fall in recent years, but not to the worst levels seen in the 1970's. In more depth, wheat is plentiful and corn stocks are tight.

Measuring market concentration divides the story into two. A diversified market exists for rice and wheat, whereas corn and soybeans are somewhat concentrated. In both cases, the U.S. and Brazil dominate with Argentina also a major producer. Global consumers of corn and soybeans are therefore strongly exposed to possible crop failure in either the US or Brazil.

We introduced a method to estimate spare capacity, i.e. additional acreage that could be planted in the next crop year. We found low spare capacity (less than 10%), except in the case of wheat. In particular, corn has fallen significantly since 2000. We noted a strong relationship between spare capacity and price.

We introduced yield-at-risk to study the global variations in yield and in particular the extent of large shortfalls. This also permitted us to put the stocks-to-use ratio in context. Again the message was of scarcity in corn and soybeans, with abundance of wheat and especially rice. Only in the case of corn, the distribution of yields for corn exhibited 'fat-tails', warning that extremely bad harvests occur more often than expected, hence our yield-at-risk figure may be an under-estimate.

Our examination of land-competition between the four crops reveals that competition is emerging between corn and soybeans for land, but not between other crops. Rice lives in isolation, neither competing for land with the other crops nor correlated in price.

In summary, the period from 1980 to 2000 seems to have been one of agricultural plenty. Since then, we have returned to greater scarcity, but no worse than that observed in the 1970's. Compared to that period, agricultural production has become greatly more

diversified internationally. Focusing on individual crops, wheat and rice show few warning signs. Soybeans and particularly corn are cause for concern, with relatively concentrated markets, low stock levels given yield risk, and minimal spare capacity. Compounding this, corn and soybeans exhibit both the highest competition for land and the highest price correlation. Thus, scarcity in one of the two will rapidly result in scarcity of the other, with a likely spike in price and volatility when this occurs.

Appendix

Definitions

- Define the set of all countries as I , with a given country denoted $i \in I$.
- Define the most recent crop year as T and an arbitrary crop year as t .
- Define area *harvested* in country i in year t as $AH_{i,t}$ with *worldwide* acreage harvested being $AH_{\Omega,t}$. Thus Ω represents ‘the entire world’.
- Similarly let Y denote yield, P denote production, I denote imports, X denote exports and C denote consumption.
- If we need to distinguish between two crops $c1$ and $c2$, we use parenthesis, for example $P(corn)_{i,t}$ denotes the production of corn in country i in year t .

Calculating The Market Concentration Indices

We use the usual Herfindahl-Hirschman calculation for the global market concentration indexes of production MCP and exports MCX as the sum of squares of each individual country’s proportion of global production and exports respectively. Using our nomenclature, for a given crop c

$$MCP(c)_{\Omega,T} = \sum_{i \in I} \left(\frac{P(c)_{i,T}}{P(c)_{\Omega,T}} \right)^2 \quad (2)$$

$$MCX(c)_{\Omega,T} = \sum_{i \in I} \left(\frac{X(c)_{i,T}}{X(c)_{\Omega,T}} \right)^2 \quad (3)$$

Calculating Spare Capacity

Our aim is to measure how much acreage could grow above the current value. Given huge uncertainty about the potential of expanding beyond the currently harvested area, we restrict our concept of maximum capacity as the highest *historically* observed.

Unfortunately most countries report only area *harvested* rather than area *planted*, and yield is also calculated based on area harvested, so we use this as the basis for our calculation. If data on area planted were available, these would be preferable since data on area harvested ignore the possibility of acreage being abandoned before harvest.

Define the ‘best’ acreage achieved for a given crop in a given country i up to year T as the highest acreage harvested in any previous year including the current year $t \leq T$, but discounting the acreage values of previous years at some low degradation rate d – we use 1% p.a:

$$B_{i,T} = \max_{t \leq T} (e^{-d(T-t)} AH_{i,t}) \quad (4)$$

Note that if this occurs in the final year then the best is simply the final year acreage:

$$B_{i,T} = AH_{i,T} \quad (5)$$

Define spare capacity per country as the best acreage minus the current acreage. Since the best could be the final year, spare capacity for each country is non-negative.

$$SC_{i,T} = B_{i,T} - AH_{i,T} \quad (6)$$

We now compute *global* spare capacity, measured as a percentage, first by aggregating spare capacity (measured in units of acreage) over all countries, then by representing this as a proportion of current global total acreage:

$$SC_{\Omega,T} = \frac{\sum_{i \in I} SC_{i,T}}{\sum_{i \in I} AH_{i,T}} \quad (7)$$

Calculating yield-at-risk

For each crop, first we fit a trendline \widetilde{Y} to smooth the yield Y . After testing various methods¹⁵, we settled on the following:

1. Let t denote the index of the yield observation, i.e. t ranges from 1 upwards to T .
2. Define the trend value \widetilde{Y}_t for years $t = \{6, \dots, T-5\}$ as an arithmetical average of 10 years' observations, centred on year t :

$$\widetilde{Y}_t = \frac{1}{10} \sum_{\tau=t-5}^{t+4} Y_\tau \quad (8)$$

3. Since we have insufficient data points to generate a similar centred average for years 1 to 5, we instead use the gradient of the *trend* yield observed between years 6 and 10, and apply it to the first 5 years. This ensures a smooth and reasonable trendline for the first 5 years, That is, let:

$$\widetilde{Y}_5 = \widetilde{Y}_6 - \frac{\widetilde{Y}_{10} - \widetilde{Y}_6}{10 - 6} \quad (9)$$

$$\widetilde{Y}_4 = \widetilde{Y}_5 - \frac{\widetilde{Y}_{10} - \widetilde{Y}_6}{10 - 6} \quad (10)$$

and so on.

4. We repeat stage 3 for the *most recent* 5 years, adjusting the formulae as appropriate.

Next we calculate the 'surprise' in yield \widehat{Y}_t for year t as the difference between observed and trend yield, so that a lower observed value than trend gives a negative surprise, and express this as a proportion of trend. We ensure the mean surprise is exactly 0 by subtracting from each value the series mean.

¹⁵ As discussed by Just and Weninger (1999), selection of a good trendline is essential when analysing variations in yield, since we are effectively examining the residuals of the fit.

$$\widehat{Y}_t = \frac{Y_t - \widetilde{Y}_t}{\widetilde{Y}_t} - \underset{t=1, \dots, T}{mean} \left(\frac{Y_t - \widetilde{Y}_t}{\widetilde{Y}_t} \right) \quad (11)$$

For our GARCH model, to estimate the stochastic variance σ_t^2 of our yield surprise series, we use the standard GARCH(1,1) updating formula of:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (12)$$

and set $\alpha_0 = 0$, $\alpha_1 = 0.1$ and $\beta_1 = 0.9$ for all crops¹⁶, setting the innovations ε_t to be our yield surprises \widehat{Y}_t , and seeding the initial variance $\sigma_{t=1}^2$ with the variance of the first 10 surprises \widehat{Y}_1 to \widehat{Y}_{10} .

To calculate the yield-at-risk at the 90% level, we simply invert the normal distribution with mean 0 and variance σ_t^2 and compute the value YaR_t having 10% of the probability mass in $(-\infty, YaR_t]$.

¹⁶ We tried estimating the GARCH parameters but found widely different results for each crop, possibly due to the low sample size. We settled on this single parameter set by visually observing the evolution of yield-at-risk.

Calculating Land Competition

We calculate a regression between the change in acreage for two crops c_1 and c_2 as described below.

We consider only those countries $i \in I$ where:

1. The country i represents at least 1% of global acreage for each crop
2. The acreage planted in the previous year was > 0 . Zero represents either ‘no data’ or ‘no planting’ in the USDA database. Given some series suddenly jump up from 0 to a moderately high value we believe 0 often represents ‘no data’ hence this first year should be omitted as an ‘acreage change’.

Then, defining the change in acreage $\Delta AH_{i,t} = AH_{i,t} - AH_{i,t-1}$, we then calculate the correlation coefficient for year t between the acreage changes observed in these countries over a rolling window comprising the most recent 5 years as:

$$x_t = \text{corr} \left\{ \Delta AH(c_1)_{i,\tau}, \Delta AH(c_2)_{i,\tau} \mid \tau \in \{t-4, \dots, t\} \right\} \quad (13)$$

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Conclusion

In Chapter 1, we examined the complex supply chains that bring commodities from their raw state, via several transformation and processing stages, to the consumer. If the raw material is easy and cheap to produce or extract, and there are no constraints in the supply chain, we proposed that the final commodity will be abundant and its price will be low and exhibit little volatility.

In contrast, there are a number of ways in which supply chains can become disrupted, including where inventory 'buffers' are abnormally low. We proposed that any of these may cause the final commodity to become 'scarce', with prices and volatility both rising.

The overall aim of this thesis was to examine this hypothesis, and in particular to examine ways to extend the analysis beyond using inventory, which is currently the main way of measuring commodity scarcity.

We began our empirical analysis in Chapter 2, studying the six base metals traded on the LME. Seasonality of either supply or demand complicates the analysis of agricultural commodities and energy commodities respectively. Since metals exhibit neither type of seasonality, they make an excellent 'base case' to study the interaction of fundamentals, price and volatility.

We used as a theoretical basis the 'theory of storage', first proposed by Working in 1933. In it he noted that as inventory levels of wheat fell to abnormally low levels, spot prices and spot price volatility rose compared with the price and volatility of longer term contracts. In essence, the market is responding to a situation of scarcity by raising prices, as would be expected in classical economics. The reason that longer-term prices are not affected by scarcity, or affected but less strongly, is that markets know that price rises incentivize both the creation of additional supply and the reduction of demand. This forms an economic mechanism for prices to mean-revert.

Although well-studied in agricultural markets, the theory of storage had, prior to our work, not been fully tested in base metals. Previous work had mainly focused on the response of commodity volatility to scarcity, rather than price.

We studied in detail the relationship between price, volatility and inventory levels. We found strong confirmation for the theory of storage.

For price, we found, as proposed by Working and described in more detail by Brennan and others, that the spread (the ratio of spot prices over 3-month prices, with technical adjustments for storage and financing costs) rose strongly during periods of low inventory. At other times, the spread was close to 0, but almost never under (the few occurrences imply a risk-free arbitrage was available). In this section, we contribute to the literature in three ways:

1. We demonstrated just how strong the relationship between spread and LME inventory was for all six base metals.
2. We noted that when inventories were expressed not in tonnes but in 'days of worldwide consumption', a very similar curve was observed in the case of all 6 base metals, with a sharp rise in spot prices beginning when inventory fell below 10 days of global consumption.
3. We noted that Chinese inventory data from the Shanghai Futures Exchange (SHFE) was reliable, to the extent that using it strengthened the relationship compared with using solely the LME inventory data. Further, we showed that inventory data from other sources was immaterial.

When examining the relationship between volatility and inventory, we noted that the relationship was somewhat muddy. However, we introduced another contribution to the literature here:

- We found that subtracting futures price volatility from spot price volatility, to expose only the 'excess' volatility of spot prices, gave a strong relationship with inventory. It is possible that the varying volatility of metals prices is partly caused by varying volatility 'transmitted' from other asset classes. Our method here helps to remove this background noise, showing that the variations in inventory fundamentals mainly affect the volatility of the spot price.

As a potential application of these relationships, we observed that those brief periods where observations had departed from the norm had a particular meaning. At these times, price and volatility were higher than expected, or correspondingly, the market was behaving as though less inventory was available than that reported by the LME. This could imply that inventory in an LME warehouse was held by someone unwilling to sell, who was 'squeezing' or

‘cornering’ the market. Although we have not seen others use the theory of storage in this way, we observe that part of Working’s original paper on wheat noted that points deviating from the relationship he observed in the early 20th century were due to known ‘corners’ in the wheat market at that time. We should of course remember that inventory can and does exist outside of the LME warehouse system, and its extent is varying and difficult to quantify. If market manipulation involved inventory outside of the LME’s warehouses, we would not detect it with this methodology.

This chapter provided the groundwork to the remainder of the thesis, by showing that in a simple, non-seasonal commodity, a strong non-linear inverse relationship involving a measure of scarcity and price is observed, with scarcity in this case being measured solely by inventory.

Chapter 3 then considered the more difficult case of electricity. Initially, it would appear that the theory of storage cannot be applied, since electricity is typically not storable, certainly not in the electricity market we studied, that of the UK.

However, studying electricity enabled us to widen the theory of storage to become more general theory. In chapter 3 we termed this the ‘extended theory of storage’. Perhaps a yet more general term would be ‘the theory of commodity scarcity’ or perhaps ‘the theory of constraint in commodities’. By calculating the amount of spare generating capacity available on a given day, and with a price database of several years, we observed a strong non-linear inverse relationship between (a) spare capacity and price, and (b) between spare capacity and price volatility.

More generally, this showed us that if we are able to measure some other feature in the supply chain that measures ‘scarcity’ or ‘constraint’, such a feature will impact price and volatility in a similar way to the standard ‘theory of storage’ relationship involving inventory.

Having found that spare capacity was a useful fundamental factor in explaining the evolution of electricity prices and volatility, we also tested whether spare capacity could be used in a model to explain the price the most widely studied of energy commodities, crude oil. We found that using an existing public estimate of spare capacity had significant explanatory

power in crude oil prices, more so (in our simple model) than the more widely used inventory figures.

Our contributions to the literature in this chapter are as follows:

1. Recognition that the 'theory of storage' effect based on inventory is just a sub-case of a wider relationship between one of perhaps many fundamental factors and the price and volatility of a commodity.
2. A demonstration that spare capacity, and not the more widely cited demand, better explains the huge day-to-day variation in electricity prices.
3. A demonstration that the spare capacity relationship is valid and useful even when inventory data are available.

Having noted the usefulness of spare capacity as another way of measuring commodity scarcity, we finally proceeded to study agricultural commodities in Chapter 4, focusing on the four most widely grown crops, namely corn, wheat, soybeans and rice.

With the yearly seasonality in agriculturals presenting a complicating factor when measuring inventory, we used yearly data samples to remove this issue, as did Working in his initial analysis for the theory of storage. This necessitated a long database; we used the period 1960-2012. The large increases in acreage, yield and production over that period made it necessary, at times, to de-trend the data.

The usual way of measuring agricultural scarcity is by measuring inventory just before the new harvest. Other existing methods of predicting scarcity require detailed micro-level analysis and large databases of individual regions' climate, water sources etc., so as to predict future agricultural productivity. We proposed to develop additional, simpler measures of scarcity using only existing historical time-series.

We developed two main metrics for agricultural products in this paper, which we feel are significant contributions to the literature:

1. A method of estimating global or national agricultural spare capacity for a given crop by estimating additional acreage that could be planted with that crop in the next

crop year. We are unaware of the econometric technique we developed having been used elsewhere; certainly we believe it is a formalization of what may have in the past been a rule of thumb. This technique could perhaps be applied to other commodities such as national-level oil production or mineral production provided that a suitable discount level was used. However, the technique seems most applicable to agricultural commodities since farmers often switch their production from one crop to another; the same could not be said of a mine or oil well.

2. An enhancement to the usual 'stocks-to-use' ratio that puts the value in better context. Specifically, for crops with highly uncertain yields, a higher level of inventory is required than for crops with more consistent yields, since inventory functions as a buffer against uncertain supply (demand in agricultural commodities typically being more predictable). The 'yield at risk' method we developed, calibrated with a GARCH model, could perhaps be simplified by taking a simple standard deviation of recent crop yields, and assuming normality and homoscedasticity (constant volatility).

Further, we proposed two additional measures of agricultural scarcity, based on analysis of land competition and market concentration. Although interesting, we believe these are not significant contributions to the literature.

Our results for the four crops over all different measures of scarcity told a similar message, that of extreme scarcity in corn, moderate scarcity in soybeans and abundance in wheat and rice.

In particular we observed once again the non-linear relationship between price and measures of scarcity, with prices rising above normal levels when the measures show high scarcity.

To draw some overall conclusions, we saw in all the cases we studied, the same non-linear effect on price when a measure of scarcity indicates scarcity. (Perhaps, instead of

‘measure of scarcity’, we should use the term ‘measure of abundance’ so it is more clear that a low numerical value means low abundance, i.e. high scarcity.)

This also highlights once again that the ‘theory of storage’ is but a sub-case under a wider ‘theory of scarcity’.

We feel we have, in particular, identified ‘spare capacity’ as a very useful and understudied measure of scarcity.

We would like to briefly mention further empirical studies we conducted which did not make it into this thesis. They are all avenues for future research.

1. We studied whether the ‘crack spread’, essentially the profit resulting from running an oil refinery, buying oil and ‘cracking’ it into its components such as gasoline and heating oil, is dependent on the spare capacity in oil refining. We might expect this to be the case – refiners would enjoy more pricing power if all refineries were already running at full capacity. We used national data from the US. The crack spread is available either as a time-series, or it can be derived from the underlying prices of crude oil, gasoline and heating oil. The ‘refinery utilization rate’ in US refineries is also available as a time series. Currently around 85%, this has been as high as 99% (summer 1997) and as low as 73-74% (1995, and September 2008 directly after the bankruptcy of Lehman brothers). Initial results showed a moderately-strong inverse relationship between spare capacity and crack spread ($R^2=0.26$, Spearman correlation = -0.51) using a monthly database from 1990 to 2012, and with the ‘321’ crack spread expressed as a proportion of crude oil prices.
2. We attempted to study spare capacity in dry bulk shipping markets, since it is widely agreed by market observers that the high price for shipping (measured by indexes such as the Baltic Dry Index) seen in 2007-2008 was caused by lack of available ships (low spare capacity). As a result, large numbers of additional ships were ordered at that time, many of which have been delivered in the period from 2010 onwards. The resulting excess capacity has kept shipping prices low since 2009, with some ships remaining ‘laid-up’ i.e. kept at anchor, because shipping rates were lower than operating costs. We also propose an additional measure of spare capacity in shipping

markets, caused by the recent trend for 'slow steaming', i.e. sailing ships at greatly lower than their maximum speed, to save fuel. This creates spare capacity since the ships have the ability to sail faster if higher shipping rates rise sufficiently to offset the higher costs, thus moving more cargo in a given time. However, we were unable to proceed with this analysis due to lack of some data series and low frequency observations in others.

3. We briefly examined commercial airline seats as an example of a transportation commodity. In the US, the 'US Air Travel Price Index' produced by the Bureau of Transportation Statistics reflects the cost of domestic-flight airline tickets, correcting for variations in itineraries etc., to reflect the 'cost of travelling'. The same organisation also publishes the 'load factor' for domestic-flight seats, i.e. the proportion of seat-miles that were actually used by a travelling customer. Our initial analysis once again showed a strong inverse relationship ($R^2=0.54$, Spearman correlation = -0.72) between price and spare capacity using a quarterly database from 1996-2011.

Our thesis raises as many questions as answers. Some of the questions it poses, and future lines of research, include:

1. Can the method of estimating spare capacity described in Chapter 4 be applied to metals? If so, what are the results for the base metals studied in Chapter 2?
2. In electricity markets with large hydro-power resources, does inventory behave in the expected way? How does this interact with spare capacity to affect prices?
3. If we build a 'futures curve' of spare capacity, for example in electricity listing those power stations likely to be built in the next several years, is this an explanatory factor in future energy prices? With some countries facing an 'energy crunch' in several years due to decommissioning of existing power stations (coal, nuclear etc.), can we forecast the future impact on price if additional capacity is not built?

4. In agricultural markets, how has our 'yield-at-risk coverage duration' (measuring the number of 'bad' years our inventory can withstand) varied over time? Does this exhibit a relationship with price, as we would expect? If so, is the relationship stronger than using the 'naïve' inventory value?
5. In agricultural markets, can we reconcile our estimates of spare capacity with what actually happened in subsequent years? We would expect spare capacity to be absorbed by the most profitable crop.
6. Since some countries are able to increase acreage by use of prior savannah, forests etc., whereas others are not, and we can estimate this by total acreage growth over time, can we use this to estimate spare capacity more accurately?
7. Can we build more accurate price prediction models incorporating spare capacity and other measures of scarcity? We could test this with 'back-casts', looking at whether we could have predicted (past) future commodity prices more accurately than the prevailing futures prices traded at the time of the forecast.
8. How do spare capacity and inventory interact? We did not formally test for any relationship (either contemporaneous or with lags) between them. We might expect them to both be related to the wider business cycle. Any relationship between them might help to cast light on building better models of price using both fundamental factors.
9. We proposed in our introduction that disruptions in the 'downstream' part of the supply chain have a more immediate effect on prices than upstream. This is intuitively the case, consider the likely hypothetical effect on gasoline prices if (a) there is a strike by tanker drivers moving gasoline from refineries to petrol-station (US: gas-station) forecourts and (b) a strike by geological engineers prospecting for future oil-rich deposits. Nevertheless, the relationship between the timeframe of the disruption and price is not always obvious: signs of political instability in a major oil-producing nation produce an immediate and large effect on spot oil prices, even though any disruption would likely affect oil that first has to be transported to market, stored, refined, stored again, and finally delivered to consumers many months later. Thus we can ask, how rapidly do disruptions at different points in the supply chain affect spot and futures prices? To what extent do downstream inventories alter the price disruptions supply chain disruptions further upstream?

To conclude, we hope that this thesis provides some small contribution towards improving our understanding of the way in which commodity fundamentals affect prices. Price forecasts are useful to many people; a better understanding of the role of fundamentals therefore allows more accurate price forecasts. Conversely if we wish that the price of a commodity should not rise excessively, a framework linking fundamentals and price helps us choose which fundamentals we should try to control. In energy or metals this may save money, in agricultural markets it may save lives.